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Prediction of Order Arrivals and Stock Outs in a Supply Chain: an Artificial Neural Network Approach

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By believing passionately in something that still does not exist, we create it.
The nonexistent is whatever we have not sufficiently desired.
Kafka F., 1883-1924.

To my parents and Nuno.

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Resumo

A capacidade de prever ruturas de stock é um tópico importante que permite, por um lado, o aumento da estabilidade de uma cadeia de abastecimento (SC) e por outro, a capacidade de reação de cada elo que a compõe. Para além disso, ter acesso a essa informação antecipadamente permite às empresas agir proactivamente de modo a evitar ruturas de stock. Nesta tese é apresentada uma metodologia, com a aplicação de redes neuronais artificiais (ANNs) para prever: (1) a capacidade de responder a novas encomendas e, caso o stock não seja suficiente, qual o tempo previsto para completar a encomenda, e (2) quais os elos que vão atingir o nível de stock que irá despoletar uma ordem de encomenda no elo anterior. Essa informação proporciona aos gestores a capacidade de agir, antecipar e gerir problemas de disrupções na SC. Foi desenvolvida uma SC recorrendo a um simulador para gerar valores e usá-los nas ANNs. Essas previsões foram aplicadas para diferentes horizontes temporais.

O primeiro desafio consiste em prever ruturas de stock no retalhista, bem como o tempo que este vai demorar a concluir cada encomenda. O método proposto atingiu uma taxa de reconhecimento superior a 99% para prever eventos no período seguinte, e para previsões de dez períodos, atingiu valores de 90%. O segundo desafio, para a previsão de novas encomendas em cada elo da SC referentes ao período seguinte, registou resultados de 97%.

Palavras-chave: Cadeia de Abastecimento, Resiliência, Redes Neuronais Artificiais, Previsão.

Abstract

Prediction of stock outs is a major issue to increase stability and reaction capacity in supply chains (SCs). Moreover, having such predicted data at the right time empowers the company to act proactively and avoid stock outs. In this thesis, it is stated a methodology, applying artificial neural networks (ANNs), to predict (1) the capacity to fulfil upcoming orders and their time in system and (2) which SC nodes will reach the re-order point and thus, require new orders upstream. That information will give the managers time to act, anticipate and cope with disruptions. It was designed a SC with a simulator to generate data and feed the ANNs. The network was trained and tested with untrained values generated by the simulator. These predictions were performed for different time horizons.

The first challenge aims to predict back orders on the retailer along with the time to finish each order. The proposed system achieved a recognition rate (RR) greater than 99% when predicting the events for the next period, and, for an interval of ten future periods, it achieved results around 90%. In the second challenge, the prediction for the next period regarding new orders through all the nodes of the SC outcome RRs of 97%.

Keywords: Supply Chain, Resilience, Artificial Neural Networks, Prediction.

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1. INTRODUCTION

The vulnerability through SCs has been increasing in the last years, not only as a result of the necessity to reduce costs but also considering the permanent focus on increasing efficiency rather than effectiveness (Jüttner, Peck, & Christopher, 2003). It means that SCs are becoming more efficient during normal times, and at the same time more exposed to factors that may cause them vulnerability.

A company that every so often fails to deliver their products on time is more likely to be overtaken by other companies. To increase competitiveness, many companies are focused on lessening the impact of disruptions rather than increasing the profits in the short term. Predict future stock outs and backorders bring reliability and stability to the companies, give the managers control over the future situations through the SC and ability to accurately manage their stocks and schedules. This control is also reflected on the status of other companies and might be crucial for keeping customer's allegiance and satisfaction. Furthermore, it increases competitiveness, not only for the company itself but also for upstream and downstream organizations and the ones non-directly connected with that SC. SCs are at some point intersected with others due to their common points: the overwhelming majority of suppliers have more than one customer and a considerable percentage of customers are furnished by different suppliers.

The steadiness in a SC is affected by a large number of sources of uncertainty. However, anticipate stock outs will empower the companies to act proactively and reduce risks, which induces higher levels of competitiveness. In comparison with the last few decades, there is a wider variety of aspects that bring uncertainty to the SC, and some of them are practically impossible to foresee, like terrorist attacks and natural disasters. Due to that unpredictability, the impacts are catastrophic. Many strategies have been identified and presented in the literature as a way to cope with unpredictability as, for example, by selecting suppliers, considering factors like localization and political instability (Mascaritolo & Holcomb, 2008), enhancing the security system (Fakoor, Olfat, Feizi, & Amiri, 2013), increasing the diversification of products and suppliers (Tang, 2006) and creating redundancy using spare capacity and inventories to cope with disruptions (Christopher & Peck, 2004).

On the other hand, there are some sources of uncertainty that, considering historical data, fit in certain curves or follow particular distributions, so the data can be extrapolated for future events. Considering these predictive sources of uncertainty and by enhancing the visibility and supervision through the SC, the resilience may also increase. Revilla & Sáenz (2014) present a case of a company that installed monitoring tools to map the SC, adding threat awareness of the potential disruptions at an opportune time. As stated by Pettit, Croxton, & Fiksel, (2013), visibility implies being aware of the status over the SC and its environment. Yet, that information may be unavailable or inadequate, which constitutes an obstacle that restricts the capacity to act in real-time to fluctuations in SCs. That is why monitoring the actions and being conscious of what happens from upstream, downstream and, eventually from other entities non-directly connected with the SC is crucial. Moreover, hiring outsourcing companies, like transportation or maintenance companies, implies that the resources are shared and may be limited. Being alert to the situation will reduce unexpected service failure. Another example is sole sourcing, which in terms of management perspective might be interesting, but may also represent a dangerous aspect in terms of resilience. In this context, it is appropriate to find a trade-off between supplier management cost and supply failure risk. Moreover, being aware of the whole SC's behaviour gives hints to adjust and redesign the SC regarding the problematic nodes and the nodes that are reducing its performance.

As stated above, SCs are enclosed by stochastic factors and situations that are hard to foresee. In most cases, the combination of all these points proves to be challenging and hard to cope with. Regarding that uncertainty, it becomes hard not only to predict future situations, but also do it in time and give managers the ability to consider the best solutions to deal with or even avoid them.

The focus of this thesis is to overcome two major challenges:

(1) Predict stock outs on the retailer and the orders' time in system – predict the capacity to fulfil promptly the upcoming orders and the time it will take to dispatch each order. That information notifies for the existence of back orders on the retailer.

(2) Predict order arrivals in each SC's node – predict which nodes will have their inventory levels below the re-order point and when. The re-orders trigger new orders upstream.

This thesis addresses these challenges by relying on an intelligent system (IS) to predict future status from historical data. The methodology begins by setting up a multi-echelon SC in a simulator to generate data to feed the IS. These data are used to teach the IS patterns and give it the ability to recognize and extrapolate to future events based on new and untrained data. Both challenges bring stability and sense of control, and since SCs are all, at some point, connected and conditioned by others, being aware of back orders and requests for new parcels will give room to plan more accurately the production management.

This thesis comprises 5 sections. In section 2 it is stated the literature related to SC management using artificial intelligence. Section 3 covers the methodology implemented on the proposed approach, and the results are presented in section 4. Conclusions are exposed in section 5.

2. STATE OF THE ART

The SC concept has been discussed intensively among practitioners and within the scientific community since the mid-eighties. Nowadays, SCs face new challenges and risks like demand fluctuation, vulnerability due to globalization, markets saturation and terrorist attacks, leading companies to establish new concepts for risk management (Jung, Blau, Pekny, Reklaitis, & Eversdyk, 2004), (Barry, 2004). Also, the markets are in constant change, which turns management and strategic planning into challenging decisions such as predict inventory levels, transportation policies, production scheduling and lot sizing. These are some of the managers' dilemmas that have to be settled regarding numerous parameters like costs, risks, time and reliability. Hult, Mena, Ferrell, & Ferrell (2011) argues that SC's uncertainty is an issue with which every manager wrestles due to the increasing complexity of the global networks, leading to a growth risk of delivering delays and quality problems.

Some organizations cope better with risks than others, mostly because they have a robust SC, commonly known as a resilient SC. Resilience can be defined as - "the ability to proactively plan and design the supply chain network for anticipating unexpected disruptive (negative) events (…) and transcending to a post-event robust state of operations, if possible, more favourable than the one prior to the event, thus gaining competitive advantage" - (Ponis & Koronis, 2012). This definition shows that resilience in SCs can be assessed in four aspects: (1) preparation for a disruptive event, (2) response to an event, (3) recovery from the event and (4) growth/competitive advantage after the event (Tukamuhabwa, Stevenson, Busby, & Zorzini, 2015). Moreover, companies ought to control and regulate their SC on a regular basis to adjust it to the constant environment variations as a way to avoid the negative outcomes (Skipper, 2008).

There are some risks taken consciously, acknowledged as "calculated risks" (Svensson, 2002). These risks are taken whilst making important decisions regarding costs, security and performance, whence it is important to establish the levels which represent the "manageable" risks the company is willing to take. However, it is not possible to achieve 0% probability of risk because of the unpredictable risks (Teuteberg, 2006).

One of the most cited and representative cases of disruptions in industry is the "Nokia-Ericsson's fire" in 2000. The fire occurred at a sub supplier's plant - Philips Electronics, in Albuquerque - New Mexico. The effects were huge because the fire flared inside of a "clean room" and took three weeks until the production started properly again. Furthermore, six months later the production rate was 50% lower and their capacity was not sufficient to supply the orders. This plant was Ericsson's and Nokia's sole supplier for that particular chip (radio-frequency chip), however, it was devastating only for Ericsson who faced a loss of $1.7 billion for that year. On the other hand, Nokia acted pro-actively, and apart from other commitments, they re-designed the chip, so it could be produced in other plants. Another step was to find alternatives to supply that chip, showing more resilience than its competitor and prospering despite this negative event (Jianxin, 2008). The disparity of outcomes made the episode so notorious that it was declared as "The fire that changed an industry" (Mukherjee, 2008).

Several strategies have the aim to improve SCs' resilience and have been displayed in literature. (Tukamuhabwa et al., 2015) based their work on the analysis of 91 papers and presented a list of 24 resilience strategies categorized as proactive or reactive. The implementation of some of those strategies implies strengthening the SC visibility to anticipate the occurrence of a disruptive event. Moreover, the ability to receive in time the warnings about potential disruptions will grant the improvement of one of the SC's resilience aspects previously referred - "preparation for a disruptive event".

According to (Sheffi & Rice Jr., 2005), there are three main ways to develop resilience: increasing redundancy, building flexibility and changing the corporate culture:

1. **Redundancy** is the effort taken by companies to increase their stock levels (extra inventory), capacity and workers. This strategy provides some breathing room to continue operating after the disruption. However, it is very expensive and prevent the organization to achieve higher levels of efficiency.

2. **Flexibility** results in better resistance to disruptions. To increase flexibility in a SC, a company may adopt standardized processes, plan to postpone and good relation with suppliers.

3. **Cultural change** concedes companies to recover quickly, and even profitably. The organizations implement this factor in their strategies by keeping their

employees informed and aware of the strategic goals, and by granting them power to make important decisions in the process.

As stated above, increasing resilience in SCs is an engagement hard to achieve due to the many factors that affect the managers' commitments. These commitments might have different repercussions depending on numerous and non-linearly related aspects. In order to predict the non-linear relations between factors that influence SCs, a simple linear model will not be sufficiently capable to cover the complexity of the problem. For that reason, Artificial Intelligence (AI) based methods have been implemented regarding their proved efficiency in SC behaviour prediction. The great development in computers in the last decades gave the means for the AI techniques to become more powerful and effective in situations that traditional approaches can hardly cope. A particular case of AI is the Artificial Neural Network (ANN), a technique that displays a good capacity to generalize from particular scenarios and solve non-linear problems. This means that ANNs can be used for situations of pattern classification and prediction. Since their appearance, ANNs have been applied to several classification and prediction problems like, for example, pattern recognition, time series forecasting or stock market prediction (Bansal, Vadhavkar, & Gupta, 1998; Bishop, 1995; Vellido, 1999). ANNs are algorithms based on the brain's structure and its acting: the information flows from neuron to neuron and past experiences are used to make new and more accurate decisions, like the process of learning in humans' brains. A remarkable ANN's feature is the ability to deal with incomplete data which constitutes an essential quality regarding all the dubieties within a SC (Bertels, Jacques, Neuberg & Gatot, 1999). SCs are exceedingly based on imprecise and inaccurate information and surrounded by sources of information that are not trivial to relate, which turns the ANNs an important step regarding forecasting, simulation, optimization and decision support enhancement. It can be particularly interesting in that matter to address issues like sales or demand forecasting, performance measurement, cost prediction, scheduling, production/supply planning, customer segmentation and order assignment (Efendigil & Önüt, 2012). ANNs are even more significant when the data is highly dependent on each other, or when it is unstable or incomplete, and these features cover exactly the problems faced in SCs.

Chen, Wee, Wang & Hsieh, (2007) demonstrate that ANNs can be used as a decision-making tool. The experiment, based on the Beer Game, applies ANNs to find out which sequence of mixed inventory policies would yield the best performances regarding the total SC cost. Efendigil & Önüt (2012) proposed an approach that combined ANNs and a fuzzy inference system (ANFIS) to predict demands and lead times in a multi-echelon SC. Also, Dong & Wen (2006) presented a method to foresee demand variation. In this case, they used recurrent neural networks and proved that this process could predict oscillations in demand more accurately than when applied the traditional feed-forward method. Aburto & Weber, (2007) carried out the same approach using a hybrid intelligent system.

Comprehensive reviews incorporating SCs and ANNs are presented in (Efendigil & Önüt, 2012; Peidro, Mula, Poler, & Lario, 2009).

As far as we know, there are no papers in literature towards the goal that it is proposed in this thesis. The majority is focused on demand forecasting, production planning and/or vendor selection. This work's aim is to provide the sense of control over the SC by predicting back orders, stock outs and upcoming requests for new orders. That information gives managers the time to adjust the plan, act pro-actively and minimise the effects that come from the inability to fulfil the demand. The fact that SCs are more and more complex leads to unpredictable and unexpected situations.

3. RESEARCH METHODOLOGY

To address the question on how the ANN techniques can be used to predict potential disruptions in a SC, we combine a multi-echelon SC simulation model, described in section 3.1, with an ANN architecture described in section 3.2.

The approach was carried out by using a simulation software (Simul8 ®) to model a SC and set the SC parameters, either stochastic or deterministic, that were contemplated to generate new data and feed the ANNs. The network was developed using Matlab programming.

3.1. The simulation model

In this thesis we considered a hypothetical SC based on a model presented in Almeder, Preusser, & Hartl, (2009), Figure 1. The SC is dedicated to a single product and consists in four nodes: supplier, production, distribution and retailer. The product flow moves downstream, and the information flow moves on the opposite way. The time between order arrivals is fixed and set with a length of one time unit. The order size is variable and follows a normal distribution with mean 40 units and standard deviation 2 units.

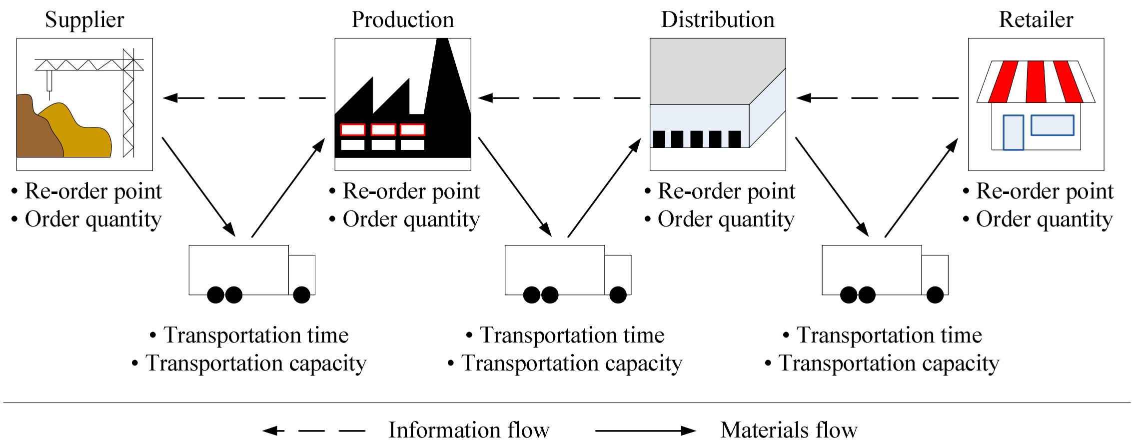

Figure 1. Supply chain model.

The retailer is the entity in charge to fulfil these orders, and whenever the re-order point is reached, an order upstream is triggered towards the distribution centre to reload the stock. The parcel sent from the distribution has a fixed quantity. If a back order occurs (the current stock is not sufficient to satisfy the order), the available quantity is sent immediately and the rest is dispatched as soon as its stock is loaded. Note that back orders lead to delays in the process, which causes queues and unwanted lead times. The ordering policy used is the *order point, order quantity* so-called (s, Q) system, in which both re-order point, s, and order quantity, Q, are fixed. It is a method with a continuous review so that it provides a stable service level, although it does not cope effectively with sudden large orders. The same policy is applied through all the nodes, i.e., the orders from the distribution, production and supplier are sent to their respective upstream node, induced by stock levels lower than the re-order point.

The echelons are connected with transports which are set with a restricted capacity and fixed transportation time. Moreover, inventories are assumed to have unlimited storage capacity, and at the top of the SC, there is a fictitious entity provided with stock capable to, unfailingly, feed the supplier. All these settings infer that the randomness resides only in the orders size on the retailer.

In the simulation, it was fixed a set of values for re-order points and quantities to order upstream for the four entities, along with the transportation times and transportation capacities. The values for some parameters were adjusted using successive iterations until reaching a service level on retailer around 90% and the service levels on the other nodes also balanced around the same values. A service level of 90% means that, under normal circumstances, 90% of the times the inventory level is enough to fulfil instantly the order and so, its time in system is equal to zero.

Regarding the outputs, it was registered the time in system of each order and the inventory levels of each echelon whenever a new order entered in the system.

3.2. Artificial Neural Network

Multi-layer perceptron is the most common type of neural networks and defines networks with three layers or more ($n \geq 3$), one input layer, one output layer and one or more hidden layers. The weights (**W**) connect neurons from consecutive layers, and these connections exhibit different values according to the importance perceived after the iteration process in the training phase. The information from the neuron is multiplied by the weights that link it to the neurons of the consecutive layer.

In the training phase it was applied the classification method. The method recognizes which is/are the class(es) that better match in a set of inputs and uses the backpropagation algorithm to perform the training. The algorithm updates the weights in each iteration until the arrangement minimises the error function (*E*). The equation 1 computes the error function which is the difference between the target (*T*) and the actual outcome (*y*). In other words, the network adjusts the weights giving more or less importance to some neurons in order to reach a desired value, *T*. Considering y^1 the neurons of the input layer, y^n the neurons of the output layer, the neurons of the i^{th} in the hidden layer(s) and that the number of neurons in each layer is k.

$$E=\frac{1}{2}\sum_{k=1}^{m^n}\left(T_k - y_k^n\right)^2 \tag{1}$$

Where m^n stands for the number of neurons on the output layer.

The complexity of some networks or an inappropriate size may lead to overfitting/overtraining. This phenomenon creates the illusion that the network is improving its performance, but, in fact, it is only memorizing the information. It means that, the error rate will be constantly decreasing for the known data, but when tested with new and untrained data, the results will not be as accurate as expected.

Along with the weights, it is considered another input, bias (*b*), only used to balance the equations. The activation function φ^i is also contemplated in the process. To calculate the output y_k^i (of a neuron *k* from the line *i*), equation 2 was applied.

$$y_k^i = \varphi^i\left(v_k^i\right) = \varphi^i\left(\sum_{j=1}^{m^{i-1}} W_{k,j}^i y_j^{i-1} + b_k^i\right) \tag{2}$$

The weights are upgraded according to equations 3 and 4:

$$W_{k,j}^{i}(n+1) = W_{k,j}^{i}(n) + \Delta W_{k,j}^{i} \tag{3}$$

$$\Delta W_{k,j}^{i} = -\alpha \frac{\partial E}{\partial W_{k,j}^{i}} = \alpha \delta_{k}^{i} y_{k}^{i-1} \tag{4}$$

Where $\alpha \in \Re_{[0.1,1]}$ is the learning rate and is also used to calculate bias, equation 5:

$$\Delta b_{k}^{i} = \alpha \delta_{k}^{i} \tag{5}$$

δ is calculated using equation 6 and its value depends on the current layer i, and if it is an hidden layer $(2 \leq i < n)$ or an output layer $(i = n)$:

$$\delta_{k}^{i} = \begin{cases} \left(T_{k} - y_{k}^{n}\right) \dot{\varphi}^{i}\left(v_{k}^{i}\right) & \text{if } i = n \\ \left(\sum_{j=1}^{m^{i+1}} \left(\delta_{j}^{i+1} W_{k,j}^{i+1}\right)\right) \dot{\varphi}^{i}\left(v_{k}^{i}\right) & \text{if } 2 \leq i < n \end{cases} \tag{6}$$

The activation function, equation 7, is an asymmetric sigmoid, so-called logistic function with output values in the range of $]0,1[$.

$$\varphi(v) = \frac{1}{1 + e^{-v}} \tag{7}$$

And its derivative $\dot{\varphi}$:

$$\dot{\varphi}(v) = \varphi(v)\left[1 - \varphi(v)\right] \tag{8}$$

The momentum term β is a parameter used to increase the speed of convergence on the training phase where $\beta \in \Re_{[0.1,1]}$. Considering that s represents the iteration number, the weights can be calculated taking into account the previous values.

$$W_{s} = W_{s-1} + \Delta W + \beta\left(W_{s-1} - W_{s-2}\right) \tag{9}$$

In this work we developed a multi-layer perceptron set with one hidden layer. As stated before the ANNs were fed with data generated in simulation runs. These data are divided in two sets: inputs and targets that will be used on the training phase. The number of neurons in the input and output layers are not fixed: they were both re-adjusted considering respectively, the past and future boundaries using some Matlab programming. After training the network, the test phase was performed with untrained data and the recognition rates (RRs) were calculated by comparing the outcomes (outputs) with the values that were returned from the simulation.

For both challenges, the inputs are the same. The neurons x_1, x_2, x_3 and x_4 represent the stock levels of each SC node, retailer, distribution, production and supplier, respectively. The input layer can either be set considering only the stock levels of the instant (t) when an order arrives in the system, or also extend the time period considering historical data. In this case, the input layer is set with all stock levels from the instant (t) to the instant $t - q + 1$, where q stands for the number of periods considered. Thus the number of neurons on the input layer is $4 \times q$, as exposed in Table 1. Figure 2 exhibits the algorithm used to obtain the input matrix. Regarding the targets, the matrices are constructed applying different algorithms depending on the considered challenge.

Table 1. Frame of inputs used in both challenges.

Period	Inputs			
$q = 1$	$x_1(t)$	$x_2(t)$	$x_3(t)$	$x_4(t)$
$q = 2$	$x_1(t), x_1(t-1)$	$x_2(t), x_2(t-1)$	$x_3(t), x_3(t-1)$	$x_4(t), x_4(t-1)$
…				
$q = 20$	$x_1(t),..., x_1(t-19)$	$x_2(t),..., x_2(t-19)$	$x_3(t),..., x_3(t-19)$	$x_4(t),..., x_4(t-19)$

Algorithm 1 Matrix of inputs depending on the number of considered periods

Input: stock levels uploaded from an excel file **data**;
the length of the file, *len;*
the number of considered periods for the inputs, *q*

Output: stock levels sorted with (*q* -1) historical data

```
Begin
  r ← q + 4
  For j = 1 To len
    row ← j + (q - 1)
    column ← 1
    For k = 1 To r
      x(j, k) ← data(row, column)
      column ← column + 1
      If (column = 5) Then
        column ← 1
        row ← row - 1
        If (row - j = q - 1) Then
          column ← 1
          row ← q
        End If
      End If
    End For
  End For
End
```

Figure 2. Algorithm applied to create the input matrices.

3.2.1. Predict stock outs on the retailer and the orders' time in system - Challenge 1

In this challenge, the goal is to anticipate the capacity to dispatch instantaneously the upcoming orders. In other words, the order time in system is zero if the stock on the retailer is sufficient to fulfil the order, and greater than zero otherwise, which means that it was not completed immediately (retailer stock out). The times in system were divided in 5 groups, Figure 3. This move reduces the variability in the targets, without lessening important information. Hence, it is possible to identify with precision the expected time to fulfil the orders. These groups will be associated to the output neurons. Each interval is associated with a neuron in the output layer. As exposed in Table 2, the neurons y_1, y_2, y_3,

y_4 and y_5 are activated according to the order time in system. The variable p represents the prediction time horizon.

The output layer has different lengths depending on the number of periods, p, to predict. Figure 4 exposes the algorithm applied to create the target matrix. The rows are set up with a length proportional to the number of periods contemplated.

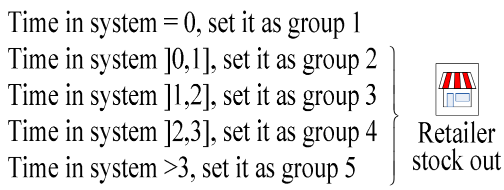

Figure 3. Intervals in which the times in system were divided, to simplify and reduce variability in the targets.

Table 2. Frame of targets used on the first challenge, arrayed according to the number of periods, *s*, to predict.

Horizon	Targets				
$p=1$	$y_1(t+1)$	$y_2(t+1)$	$y_3(t+1)$	$y_4(t+1)$	$y_5(t+1)$
$p=2$	$y_1(t+1)$, $y_1(t+2)$	$y_2(t+1)$, $y_2(t+2)$	$y_3(t+1)$, $y_3(t+2)$	$y_4(t+1)$, $y_4(t+2)$	$y_5(t+1)$, $y_5(t+2)$
…					
$p=15$	$y_1(t+1),\ldots,$ $y_1(t+15)$	$y_2(t+1),\ldots,$ $y_2(t+15)$	$y_3(t+1),\ldots,$ $y_3(t+15)$	$y_4(t+1),\ldots,$ $y_4(t+15)$	$y_5(t+1),\ldots,$ $y_5(t+15)$

Algorithm 2 Matrix of orders' time in system

Input: orders' time in system, *target,* uploaded from an excel file *A*, the number *q* of historical data considered for inputs

Output: matrix *t* arranged heeding the number *p* of periods to predict

```
Begin
  len ← length (target)
  a ← n + 1
  row1 ← 0
  For j = n + 1 To (p * len - 1)
      t(row1 +target(a)+ 1, k) ← 1
      conta ← conta + 1
      a ← a + 1
      row1 ← row1 + 5
      If (conta = p) Then
         conta ← 0
         row1 ← 0
         k ← k +1
         a← a - p +1
      End If
  End For
End
```

Figure 4. Algorithm applied to create the target matrices for the first challenge.

To perform predictions for the next period (p = 1), the architecture exhibits five neurons in the output layer, one neuron for each interval, Figure 5. If the intention is to extend the time horizon, the layer size will be $5\times p$. Figure 5 shows the architecture of the network used in this process, where *A* stands to distinguish the outputs of this challenge from the outputs of challenge 2.

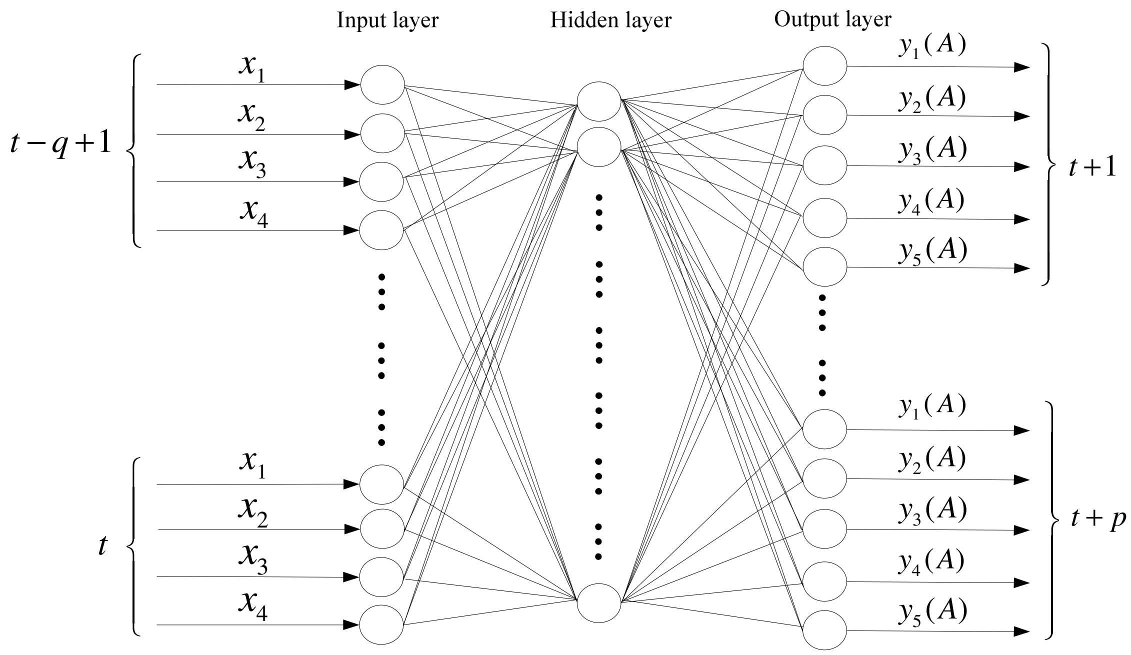

Figure 5. ANN architecture used approach to predict orders' time in system.

3.2.2. Prediction of order arrivals in each SC's node - Challenge 2

The entities that reach their re-order point, place a command for new orders upstream. The network is able to foresee when and in which nodes these situations will happen. As stated before, the inputs represent the stock levels of each entity. To organize the targets, the values were set in groups of five neurons, Table 3, in which the first four are activated when their respective entity reaches the re-order point. In this case, each neuron represents one different echelon, y_1 will turn to 1 if the stock level on the retailer is expected to be below the re-order point, and the same for the neurons y_2, y_3 and y_4 regarding the distribution, production and supplier nodes, respectively. The fifth neuron, y_5 is considered to be a control neuron, and it is activated when none of the other neurons were activated in that particular period. Figure 6 presents the algorithm that creates the target matrices for this challenge. In Figure 7 it is presented the architecture of the network, and how the size of the input and target layers vary, likewise in the first challenge.

Table 3. Frame of targets used on the first approach, arrayed according to the number of periods, *p*, to predict.

Horizon	Targets				
$p=1$	$y_1(t+1)$	$y_2(t+1)$	$y_3(t+1)$	$y_4(t+1)$	$y_5(t+1)$
$p=2$	$y_1(t+1)$, $y_1(t+2)$	$y_2(t+1)$, $y_2(t+2)$	$y_3(t+1)$, $y_3(t+2)$	$y_4(t+1)$, $y_4(t+2)$	$y_5(t+1)$, $y_5(t+2)$
…					
$p=7$	$y_1(t+1),...,$ $y_1(t+7)$	$y_2(t+1),...,$ $y_2(t+7)$	$y_3(t+1),...,$ $y_3(t+7)$	$y_4(t+1),...,$ $y_4(t+7)$	$y_5(t+1),...,$ $y_5(t+7)$

Algorithm 3 Matrix of new orders within the SC

Input: stock levels uploaded from na excel file *A*, number of periods to predict *p*, the re-order points *rp_1*, *rp_2*, *rp_3*, *rp_4*, for retailer, distribution, production,and supplier, respectively and represented as *rp_x*.

Output: matrix *t* with binary regarding the new orders in each entity arranged heeding the number of periods to predict.

```
Begin
  A1 ← A(:,1)
  A2 ← A(:,2)
  A3 ← A(:,3)
  A4 ← A(:,4)
  len ← length(A)
  len1 ← p * len
  line ← 5 * p
  For i = n+1 To len1
    row ← 1
    While row<=p
      control←0
      If Ax(j-1) > rp_x && Ax(j) <= rp_x ||
        Ax(j-1) >= rp_x && Ax(j) < rp_x Then
        row1 ← row1+1
        t(row1,column1) ← 1
        control ← 1
      Else
        row1 ← row1+1
      End If
      If control = 0 Then
        row1 ← row1+1
        control ← 0
      End If
      If row1 = linha Then
        row1 ← 0
        column1 ← column1 +1
      End If
    End While
  End For
End
```

Figure 6. Algorithm applied to create the target matrices for the second challenge.

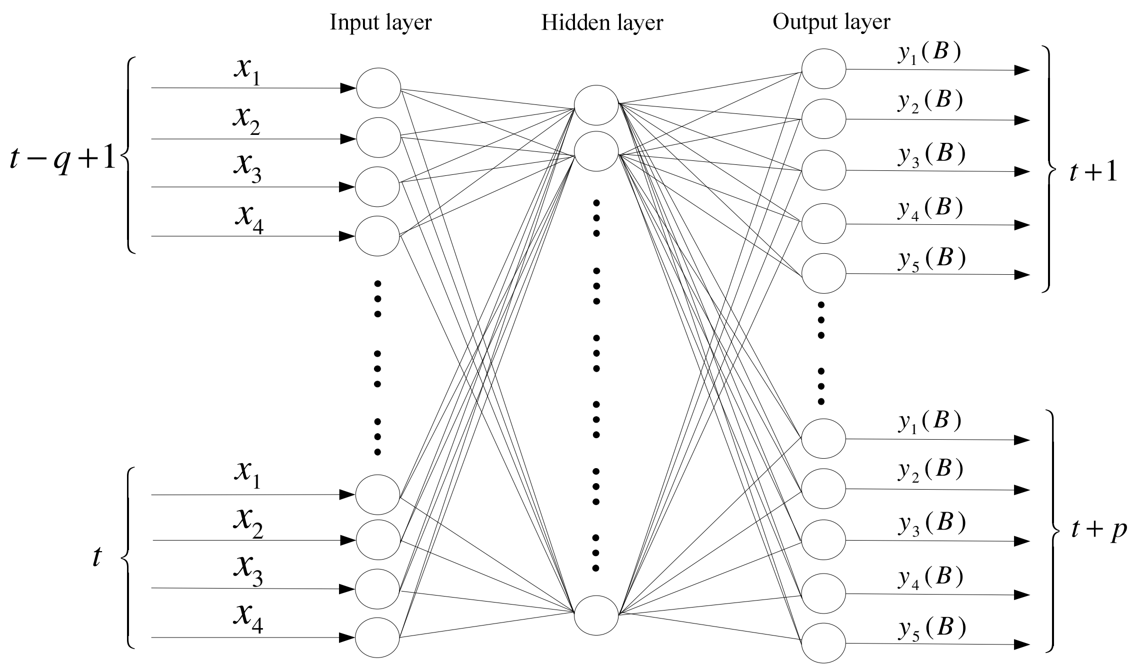

Figure 7. ANN architecture use to predict new orders through the SC

4. EXPERIMENTS AND RESULTS

The sample used to train the ANNs comprised the information of 216000 different periods of time generated by the simulator. The tests were performed with a sample with data regarding 24000 periods generated with different runs, from untrained data.

4.1. Predict stock outs on the retailer and the orders' time in system - Challenge 1

The results from these tests are displayed in Figure 8. It exposes the evolution of this process, where each line represents a different time horizon (*p*), i.e., the number of periods to predict. The points linked stand for different numbers of past periods considered for the input layer. For instance, when the number of inputs is six ($q = 6$), all stock levels, from the present time to five previous times, are taken into consideration. All the values used to build that graph are assembled in Table 4.

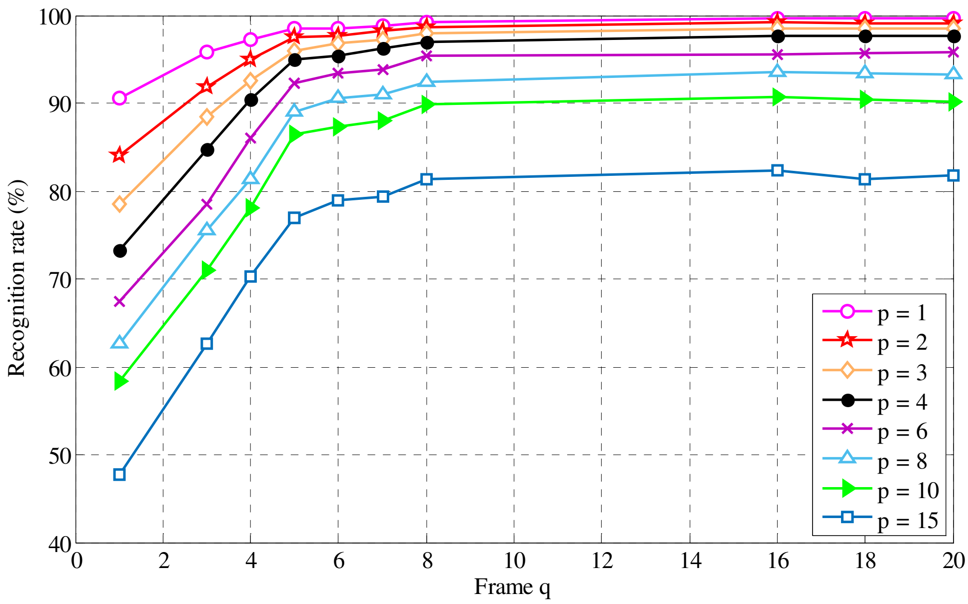

Figure 8. Recognition rates considering different numbers of inputs and different horizon times to predict the orders' time in system.

As shown in Figure 8 regardless the number of periods to predict, when it is used five periods for the input $(q = 5)$ the graph becomes steady, which means that enlarging the number of historical data to values greater than five will not result as a performance improvement. In fact, it is noticeable a slight deflection in some line charts concerning larger values of q, which denotes that exceeding information may bring confusion and, therefore, lower RRs. RRs denote the efficacy of the network to predict the future events.

Furthermore, this process performed predictions with outstanding outcomes: for predictions of one period it achieved RRs greater than 99%, and over than 98% for the three next periods (p = 3). To predict ten periods (p = 10) the results were greater than 90%, and for fifteen, (p = 15) it reached RRs over than 80%.

The fact that most parameters were set as deterministic induces a considerable reduction of the variability in this SC, which enabled the network to achieve high recognition levels. In Table 4 it is presented the values from the runs that were used to plot the graph in Figure 8.

Table 4. Recognition rates for the orders' time in system considering different numbers of inputs and period times to predict.

	$q = 1$	$q = 3$	$q = 4$	$q = 5$	$q = 6$	$q = 7$	$q = 8$	$q = 16$	$q = 18$	$q = 20$
$p = 1$	90.5	95.8	97.3	98.5	98.5	98.8	99.2	99.6	99.6	99.5
$p = 2$	84.1	91.8	94.9	97.5	97.7	98.2	98.7	99.2	99.1	99.1
$p = 3$	78.5	88.5	92.6	96.0	96.8	97.2	97.9	98.5	98.5	98.5
$p = 4$	73.2	84.8	90.4	95.0	95.4	96.3	96.9	97.6	97.6	97.6
$p = 5$	69.6	81.6	89.7	94.7	94.7	94.5	96.0	96.7	96.6	96.7
$p = 6$	67.5	78.5	86.0	92.2	93.4	93.8	95.4	95.6	95.7	95.8
$p = 7$	64.5	78.3	84.1	90.6	92.0	92.6	92.6	94.7	94.7	94.6
$p = 8$	62.6	75.6	81.4	89.0	90.6	91.0	92.4	93.6	93.4	93.2
$p = 9$	60.6	73.0	80.7	87.5	89.4	89.3	91.0	92.1	91.7	91.5
$p = 10$	58.3	71.0	78.1	86.4	87.3	88.0	89.8	90.7	90.4	90.2
$p = 15$	47.7	62.6	70.3	77.0	78.9	79.4	81.4	82.3	81.4	81.8

The challenge 1 was performed again, varying the information used for the inputs. In this case, instead of involving all the inventory levels, it was used, only the information of the stock levels on the retailer. Figure 9 compares the results of both experiments the predictions of one and three periods, drawn in dotted line with the results from the experiment that used only the information of the retailer and, drawn in solid line the results using data of the four inventory levels. For predictions of six and ten periods, the results are exhibited in Figure 10. Table 5 and Table 6 display the values that returned from the simulations that used, as input, the retailer's inventory levels.

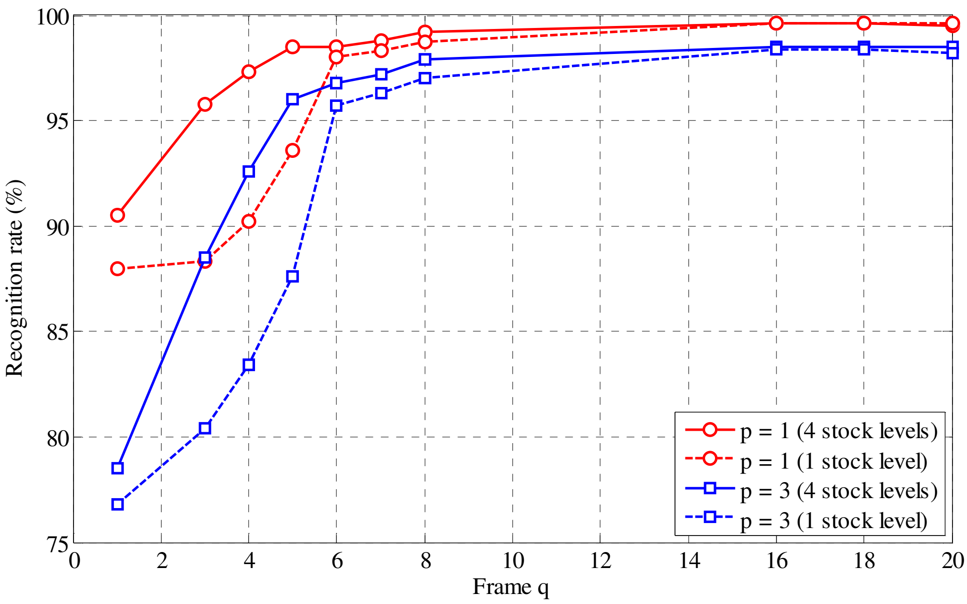

Figure 9. Comparison between the recognition rates attained when using, as inputs, the inventory levels of four entities and using only one inventory level to predict one and three periods.

Table 5. Recognition rates for the orders' time in system considering only the inventory level in the retailer.

	q=1	q=3	q=4	q=5	q=6	q=7	q=8	q=16	q=18	q=20
p=1	88.0	88.3	90.2	93.6	98.0	98.3	98.7	99.6	99.6	99.6
p=3	76.8	80.4	83.4	87.6	95.7	96.3	97.0	98.4	98.4	98.2

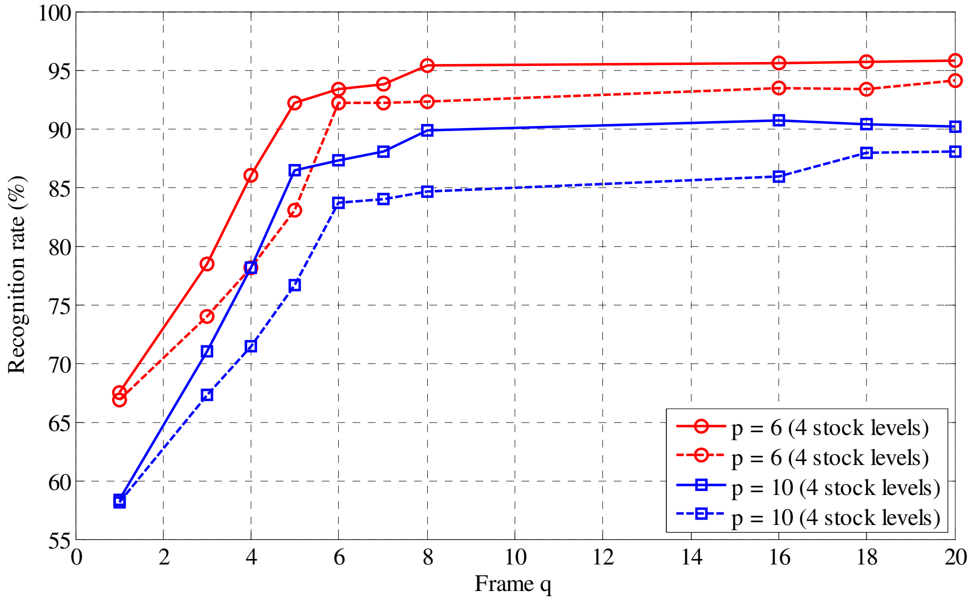

Figure 10. Comparison between the recognition rates attained when using, as inputs, the inventory levels of four entities to predict six and ten periods.

Table 6. Recognition rates for the orders' time in system considering only the inventory level in the retailer.

	q = 1	q = 3	q = 4	q = 5	q = 6	q = 7	q = 8	q = 16	q = 18	q = 20
p = 6	66.9	74.0	78.1	83.0	92.2	92.2	92.3	93.5	93.3	94.1
p = 10	58.1	67.3	71.4	76.6	83.7	84.0	84.6	85.9	87.9	88.0

The graphs bring out the difference between both experiments. As expected, the outcomes are better when it is used data from all the stocks. Although, and again because of the lack of uncertainty in the SC model, the ANNs understand the pattern and are capable of making predictions of one period (p = 1) and three periods (p = 3) with similar accuracy when using larger numbers of historical data $q \geq 5$. On the other hand, the results of the different experiments for larger horizons, $p = 6$ and $p = 10$, do never intersect. This reinforces the point introduced previously: the importance of the visibility through the SC and the awareness of the status on the other entities that can affect the performance of all the downwards echelons, also known as bullwhip effect.

The results from the challenge 2 are expressed in Figure 11. The interpretation follows the same parameters of the previous one: each line stands for the RRs for performances with different time horizons (p) and the number of periods considered for the inputs (q).

4.2. Prediction of order arrivals in each SC's node - Challenge 2

As shown in Figure 11, the RRs were consistent for each horizon time. For predictions of the next period (p = 1), the network performed RRs of 97%, to predict two periods (p = 2) the rates were around 85%. Yet, for time horizons of three periods (p = 3) the network was able to predict correctly 75% of the times. For all of the prediction horizons, the major improvement in the performance was when, it was considered two periods (q = 2), t and t - 1, instead of considering only the current inventory levels (q = 1). This means that, for this experiment, it is irrelevant to extend the historical data, once the outcomes when using only two periods (the current and the previous periods) are practically the same compared with the results from larger periods. When analysing Figure 11, it is possible to infer that the increment of one period in the prediction horizon time causes a decay in the RRs of all the predictions around 10-15%. The values of the RR for this challenge are exposed in Table 7.

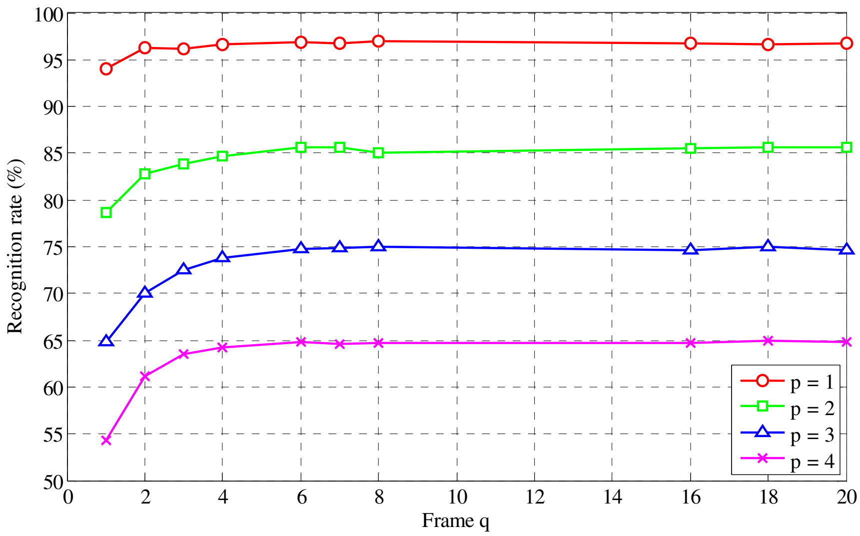

Figure 11. Recognition rates considering different numbers of inputs and different horizon times to predict the new orders within the SC.

Table 7. Recognition rates for new order within the SC considering different numbers of inputs and period times to predict.

	q = 1	q = 3	q = 4	q = 5	q = 6	q = 7	q = 8	q = 16	q = 18	q = 20
$p = 1$	94.0	96.3	96.1	96.6	96.9	96.8	97.0	96.8	96.6	96.7
$p = 2$	78.7	82.8	83.9	84.7	85.6	85.6	85.1	85.5	85.6	85.6
$p = 3$	64.8	70.0	72.5	73.8	74.8	74.9	75.0	74.6	75.0	74.7
$p = 4$	54.3	61.2	63.5	64.3	64.8	64.6	64.7	64.7	65.0	64.8
$p = 5$	49.7	53.0	54.0	55.0	55.3	55.3	55.4	55.7	55.5	55.7
$p = 6$	40.6	43.4	44.6	45.4	46.9	47.0	46.9	46.8	47.3	47.3
$p = 7$	33.4	36.8	37.0	39.2	39.9	40.1	39.8	40.3	40.4	40.6

5. CONCLUSIONS

This study addressed two major challenges. Challenge 1 consists in the prediction of back orders in the most downstream SC node (retailer), i.e., the system predicts for a certain time horizon if the upcoming orders will be instantaneously fulfilled and if not, how long it will take to finish them. In challenge 2 the system is able to give warning signs for upcoming orders to the managers of the different echelons. This process provides, apart from the sense of control over the situations, time for the managers to act pro-actively in a way to avoid disruptions and service failure. These predictions are challenging because the conditions that affect SCs are not linear. In this globalized world, SCs are all intersected and it turns to be impossible to consider so many variables using linear models. For these reasons, IS, and particularly, ANNs are an essential tool to help managers to control and handle events that reduce the efficiency through a SC. Regarding the challenge 1, the outcomes were remarkable: the RR was greater than 99.5% for predictions of the next period, over than 98% for predictions of the three next periods, 90% for predictions with a time horizon of ten periods, and nearly 82% for predictions of fifteen periods. These results were compared with a new experiment, using as input, only the information of the stock levels in the retailer. In that experiment, the results for larger time horizons were inferior, which proved that visibility in SCs are important and increase prediction accuracy. In challenge 2, the results were 97% for predictions for the next period and 75% for a time horizon of three periods. As the time horizon is enlarged the RR decreases around 10-15% for each time period added. Nonetheless, it was proved with this thesis that ANNs have features that enable their applicability in this domain.

As future work, research efforts will be dedicated to (1) introduce complexity in the SC model by adding new entities, types of products and variability and (2) use recurrent neural networks to cover that complexity.

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