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Improving Supply Chain Visibility With Artificial Neural Networks

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Abstract

The vulnerability of supply chains has been increasing and to properly respond to disruptions, visibility across the supply chain is required. This paper addresses these challenges by relying on the use of artificial neural networks to predict the capacity of a simulated supply chain to fulfil incoming orders and to anticipate which supply chain nodes will receive an order for the next period. To assess the effectiveness of the approach two experiments were conducted. The findings contribute to the understanding of on how artificial neural networks can be applied to reduce the vulnerability of supply chains.

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Keywords: Supply chain, visibility, Artificial neural networks, simulation, experimental

1. Introduction

The vulnerability of supply chains has been increasing in the last years, not only because of the necessity to reduce costs but also because of the permanent focus on increasing efficiency rather than effectiveness [1]. The negative consequences of supply chain disruptions are diverse. Additionally, to financial losses, a damage of reputation can occur. To increase competitiveness, companies are more and more focused on lessening the impact of disruptions. Therefore, predicting stock outs brings reliability and stability to companies, giving managers the ability to accurately manage their supply chain (SC) operations. This control is crucial for keeping customer's satisfaction.

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Furthermore, it increases competitiveness, not only for the company itself but also for their upstream and downstream business partners. The capacity to anticipate events empowers companies to act proactively and reduce risks, which induces higher levels of competitiveness.

Many risk mitigation strategies have been identified and presented in the literature, for example, by selecting reliable suppliers [2], enhancing the security system [3], increasing the diversification of products and suppliers [4] and creating redundancies to cope with disruptions [5]. However, there are other sources of uncertainty that, based on historical data, can be extrapolated and by enhancing the visibility through the SC, an increase in resilience can be achieved.

Supply chains are exposed to a variety of risk sources that are hard to foresee. Moreover, the combination of all those risk sources is hard to cope with. 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, being aware of others actor's behavior can give precious hints on how to adjust and redesign the SC regarding problematic hotspots. That would allow SC managers to predict events that could negatively affect the SC performance, assisting the companies in the decision-making processes, cope with uncertainty and reduce the impact of future disruptions. However, many companies still suffer from a lack of visibility, and despite extensive research, the quantification methods to increase SC visibility are still ambiguous [6].

This paper addresses this problem by combining a SC simulation model with an artificial neural network. The methodology begins by setting up a multi-echelon SC in a simulator to generate data to feed the artificial neural network. That data is used to teach the artificial network and give it the ability to recognize and extrapolate to future events based on new and untrained data. The effectiveness of the approach, in terms of recognition rate, is assessed performing two experiments.

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

2. Literature Review

The SC concept has been discussed intensively among practitioners and within the scientific community since the mid-eighties. Since markets are in constant change, decisions such as managing inventory levels, transportation, production scheduling and lot sizing are more and more challenging decisions. However, there are some risks that are taken consciously, acknowledged as "calculated risks" [7]. 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.

Considering these sources of uncertainty and by enhancing the visibility through the SC, it has the potential to reduce the adverse effects of a SC disruption [8] and to improve SC resilience [9]. Visibility, in terms of identifying and understanding inventory and demand levels across the SC [10] improves an organization's capability to process information. Specifically, visibility allows to access useful information around the products' movement. Greater visibility, created through improved knowledge and understanding of inventory and demand levels, allows organizations to proactively manage potential risks in their SC.

Some organizations cope better with risks than others, mostly because they have resilient supply chains. Resilience can be defined as "the ability to proactively plan and design the SC network for anticipating unexpected disruptive (negative) events (…) and transcending to a post-event robust state of operations, if possible, more favorable than the one prior to the event, thus gaining competitive advantage" [11]. This definition shows that resilience in supply chains 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 [12]. Moreover, companies ought to control and regulate their supply chains on a regular basis to adjust it to the constant environment variations to avoid the negative outcomes [13].

Several strategies have the aim to improve supply chains resilience and have been presented in literature. A recent review analyzed 91 papers and presents a list of 24 resilience strategies categorized as proactive or reactive [12]. 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 supply chains resilience aspects previously referred - "preparation for a disruptive event". As stated above, increasing resilience in supply chains is hard to achieve due to the many factors that affect managers' decisions. To predict the relations between factors that influence SC resilience, simple linear models are not capable to deal with the complexity surrounding supply chains [14].

The great development in computer technology in the last few decades gave the means for the artificial intelligence (AI) techniques to become more powerful and effective in situations that traditional approaches can hardly cope [15]. A case of AI is the artificial neural network, a technique that presents a good capacity to generalize from specific scenarios, solve non-linear problems and have been applied to several problems: pattern recognition, time series forecasting, performance measurement, cost prediction, scheduling, production/supply planning, customer segmentation and order assignment [15, 16, 17, 18].

Artificial neural networks 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 artificial neural network feature is the ability to deal with incomplete data which constitutes an essential quality regarding all the dubieties within a SC [19].

Since the management of supply chains is mainly based on incomplete and inaccurate information and is surrounded by different sources of information that are not trivial to relate, turns the artificial neural network an important tool regarding decision support. Artificial neural networks are even more significant when the data are highly dependent on each other or when they are unstable or incomplete. These artificial neural network features cover exactly the problems faced in supply chains. [20] identified a positive side from the scarcity of historical data. The proposed system distinguishes unexpected events from normal events with base on the distinctive features of the negative events. [21] developed a methodology in which the first step was to reproduce and model a SC applying system dynamics. In the second step, artificial neural networks were used to detect changes in the SC behavior due to external and/or internal factors. [22] conducted an experiment, based on the Beer Game, applies artificial neural networks to find out which sequence of mixed inventory policies would yield the best performances regarding the total SC cost. [18] proposed an approach that combined applies artificial neural networks and a fuzzy inference system to predict demands and lead times in a multi-echelon SC. [23] in a research where control and synchronization of chaotic supply chains is applied with intelligent approaches the computer simulations show that the proposed approach is very effective for the control and synchronization of chaos in SC systems. Comprehensive reviews incorporating supply chains and artificial neural networks are presented in [18] and [24].

However, most of the research focus on simplified supply chains which are far from the complexity of real environments. Therefore, this paper addresses that challenge, relying on artificial neural network to predict future status from historical data, trying to understand how artificial neural networks can be used to predict potential disruptions in supply chains. It's believed that information would give managers the capability to adjust plans, and therefore minimize the effects that come from their inability to fulfil demand.

3. Research methodology

To address the question on how the artificial neural networks can be used to predict the capacity of the simulated SC to fulfil incoming orders for the next upcoming period, we combine a multi-echelon SC simulation model, described in section 3.1, with an artificial neural network architecture described in section 3.2. The simulation software Simul8 ® was used to model a SC and set the parameters that were latter used to feed the artificial neural network. The artificial neural network was developed using Matlab programming.

3.1. Simulation model

In this paper, we considered a hypothetical SC based on a model previously presented by [21], Fig. 1. The SC model is dedicated to a single product and consists in four nodes: supplier, production, distribution and retailer. 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 a mean of 40 units and standard deviation of 2 units. The values of these parameters were selected along with a set of other values related to the four nodes: re-order points, quantities to order upstream, transportation times and transportation capacities for the four nodes. Those values were adjusted using successive iterations until it was reached a service level in the retailer around 90% and the service levels on the other nodes of the SC also balanced around the same values.

The retailer is the entity in charge to fulfil the orders, and whenever the re-order point is reached, an order is placed towards the distribution center to refill the inventory. The parcel sent from the distribution center is a fixed quantity. If a back order occurs (the current inventory is not sufficient to satisfy the order), the available quantity is sent immediately and the rest is dispatched as soon as its inventory is loaded. 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 could provide 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 inventory levels lower than the corresponding re-order point.

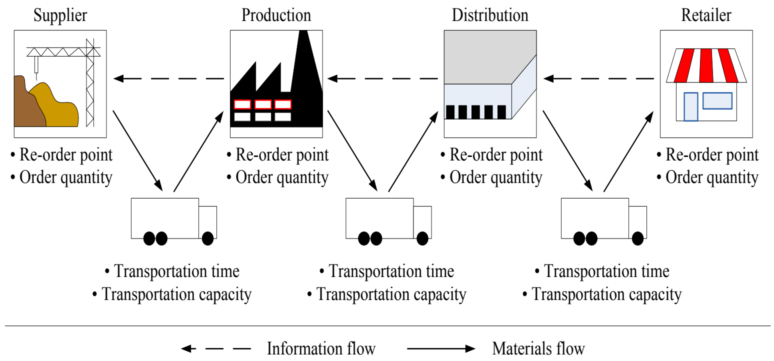

Fig. 1. Supply chain model.

The echelons are connected through a transport mode which is set with a restricted capacity and fixed transportation time. Moreover, warehouses are assumed to have unlimited storage capacity, and at the beginning of the SC, there is an entity holding enough inventory capable to feed the supplier. All these settings infer that the uncertainty in the SC comes from the orders size that the retailer must deliver. 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

In this work, we developed a multi-layer perceptron set with one hidden layer. Multi-layer perceptron is the most common type of neural networks for 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.

As stated before the artificial neural network was fed with data generated in simulation runs. 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 were calculated by comparing the outcomes (outputs) with the values that were returned from the simulation.

For both experiments, the inputs are the same. The neurons x_1, x_2, x_3 and x_4 represent the inventory levels of each SC node, retailer, distribution, production and supplier, respectively. The input layer can either be set considering only the inventory levels of the instant t when an order arrives in the system, or extending the time period considering historical data. In this case, the input layer is set with all inventory levels from the instant t to the instant $t - q + 1$, where q stands for the number of periods considered.

In experiment 1 the goal is to anticipate the capacity to dispatch instantaneously the upcoming orders. In other words, the time the order stays in system is zero if the inventory at the retailer is sufficient to fulfill that order, and greater than zero otherwise, which means that it was not satisfied immediately (retailer stock out). It is possible to identify with precision the expected time to fulfill the orders. The variable p represents the prediction time horizon. The output layer has different lengths depending on the number of periods, p, to predict.

In the experiment 2 the entities that reach their re-order point, place a new order upstream. The network can foresee when and in which nodes these situations will happen. As stated before, the inputs represent the inventory levels of each entity. To organize the targets, the values were set in groups of five neurons, 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 inventory 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. A fifth neuron, will act as a control neuron, and it is activated when none of the other neurons were activated in that period.

4. Experiments and results

The sample used to train the artificial neural network 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. Experiment 1

The results from these tests are displayed in Fig. 2. 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 inventory levels, from the present time to five previous times, are taken into consideration.

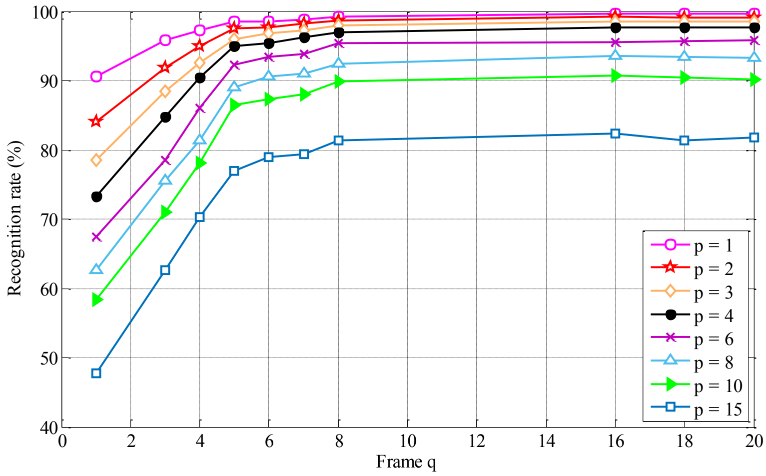

Fig. 2. Recognition rates considering different numbers of inputs and different horizon times to predict the orders' time in system.

As shown in Fig. 2 regardless the number of periods to predict, when five or more periods are used for the input ($q \geq 5$) the recognition rate tends to stabilize, which means that enlarging the historical data to five or more time periods will not result in substantial performance improvement. In fact, it is noticeable a slight deflection in some line charts concerning larger values of q, which denotes that excess of information regarding historical data may bring confusion and, therefore, lower recognition rate (the recognition rate indicates 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 a recognition rate greater than 99%, and over than 98% for the three next periods (p = 3). To predict ten periods ahead (p = 10) the results were greater than 90%, and for fifteen (p = 15) it reached a recognition rate over 80%.

The fact that most parameters were set as deterministic induces a considerable reduction of the variability in this SC, which explains how the network could achieve such high recognition rate levels. It was then decided to conduct the experiment 1 again but the information used for the inputs was changed: instead of using as input all the inventory levels, it was used, only the information regarding the inventory level on the retailer. Fig. 3 compares the results of both experiments for 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.

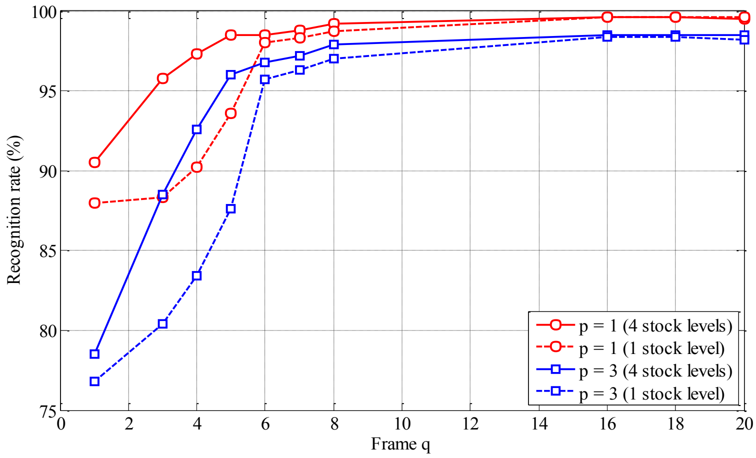

Fig. 3. Comparison between the recognition rates attained when using, as inputs, the inventory levels of four entities and using only one inventory level to predict one and three periods.

For predictions of six and ten periods, the results are exhibited in Fig 4.

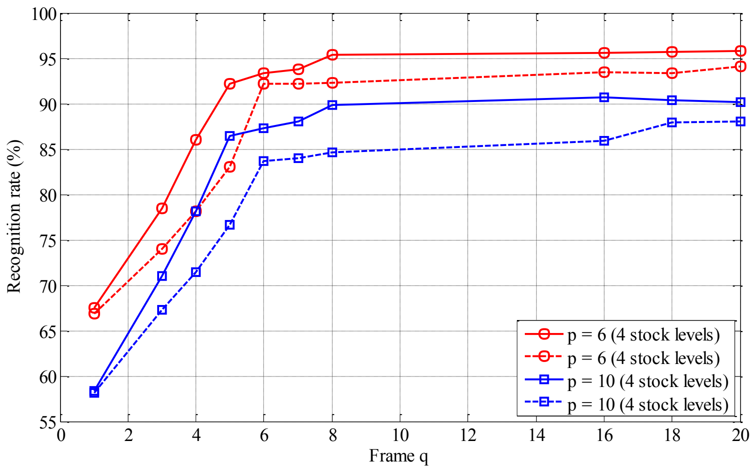

Fig. 4. Comparison between the recognition rates attained when using, as inputs, the inventory levels of four entities to predict six and ten periods.

The Fig. 3 and Fig. 4 bring out the difference between both experiments. As expected, the outcomes are better when the data from all the inventory levels are available/visible. The artificial neural network is able to understand the patterns and is capable of making predictions for one period (p = 1) or for three periods (p = 3) with similar accuracy when using larger numbers of historical data q ≥ 6. 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.

4.2. Experiment 2

In experiment 2 we will try to foresee which entities will reach their re-order point and place a new order upstream and, as stated before, the inputs represent the inventory levels of each entity. The results from this experiment are expressed in Fig. 5. The interpretation is similar to the previous one: each line stands for the recognition rate for experiments with different time horizons (p) and the number of periods considered for the inputs (q).

As shown in Fig 5, the recognition rate were consistent for each horizon time. For predictions of the next period (p = 1), the network performed a recognition rate of 97%, to predict two periods (p = 2) the rates were around 85%. Yet, for time horizons of three periods (p = 3) the neural network was only able to predict correctly 75% of the times. For all the prediction horizons analyzed, the major improvement in the performance was achieved when two periods were considered (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 substantially 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. Moreover, when analyzing Fig. 5, it is possible to infer that the increment of one period in the prediction horizon time causes a decay in the recognition rate of all the predictions around 10-15%.

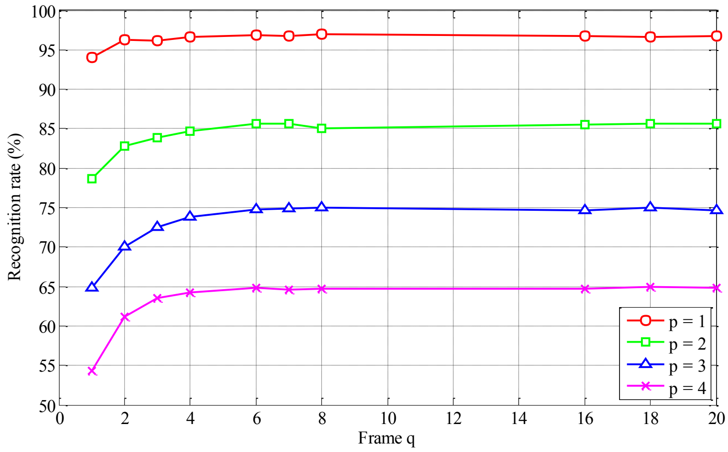

Fig. 5. Recognition rates considering different numbers of inputs and different horizon times to predict the new orders within the SC.

5. Conclusions

We argue that by enabling visibility, situations that could lead to disruptions in the SC can be identified and defused long before they reach a critical state. This paper addresses that question by relying on artificial neural networks to predict future status from historical data. A multi-echelon SC was developed in a simulator to generate data that could feed the IS. That data was used to teach the IS and give it the ability to recognize and extrapolate to future events based on new and untrained data.

In experiment 1 the artificial neural network tries to predict, 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 experiment 2 the artificial neural network tries to foresee which entities will reach their re-order point and place a new order upstream. This process provides, apart from the control/visibilty over the SC, time for the managers to act pro-actively to avoid disruptions and service failures. These predictions are relevant because the conditions that affect supply chains are dynamic and in this globalized world turns to be impossible to consider all relevant variables using traditional linear models.

Regarding the experiment 1, the outcomes were remarkable: the recognition rate was greater than 99.5% for predictions for the next period and over 98% for predictions for the three next periods. These results were compared with a new experiment, using as input only the information of the inventory level in the retailer. In that experiment, the recognition rate for larger time periods were smaller, which proved that visibility in supply chains is important and increases prediction accuracy. In experiment 2, the results were 97% for predictions for the next period and 75% for a time horizon of three periods. As the time period is enlarged the recognition rate decreases around 10-15% for each time period that is added. Moreover, we can conclude that it is irrelevant to extend substantially 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. Therefore, we can conclude that artificial neural networks can be used to predict potential disruptions in supply chains.

As future work, research efforts will be dedicated to (1) introduce complexity in the SC model by adding new nodes, types of products, additional sources of uncertainty like variability in transportation times, transportation capacities and the processing time in each entity, and (2) perform the same challenges but using a lower sample size to train the network and use recurrent neural networks to cover that complexity.

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References

[1] J. H. Thun, D. Hoenig, Int. J. Production Economics. 131 (2011) 242-249
[2] U. Jüttner, H. Peck, M. Christopher, Supply Chain Risk Management: Outlining an Agenda for Future Research. Int. J. of Logistics, 6 (2003), 197–210.
[2] W. Chang, A. E. Ellinger, J. Blackhurst, The Int. J. of Logistics Management. 26 (2015) 642-656.
[3] A. M. Fakoor, L. Olfat, K. Feizi, M. Amiri, J. of Basic and Applied Scientific Research. 3 (2013) 537–544.
[4] C. S. Tang, Int. J. Production Economics. 103(2006) 451–488.
[5] K. A. Marley, P. T. Ward, J. A. Hill, Supply Chain Management: An Int. J. 19 (2014) 142–152.
[6] Y. Lee, S.C. Rim, Mathematical Problems in Engineering, 2016 1-11.
[7] G. Svensson, Int. J. of Logistics Research and Applications. 5 (2002) 13–43.
[8] U. Jüttner, S. Maklan, Supply Chain Management: An Int. J. 16(2011) 246-259.
[9] J. C. Blackhurst, C. W. Craighead, D. Elkins, R. B. Handfield, International J. of Production Research. 43 (2005) 4067–4081.
[10] M. J. Braunscheidel, N. C. Suresh, J. of Operations Management 27 (2009) 119–140
[11] S. T. Ponis, E. Koronis, J. of Applied Business Research. 28 (2012) 921–930.
[12] B. R. Tukamuhabwa, M. Stevenson, J. Busby, M. Zorzini, Int. J. of Production Research. 53(2015) 1–32.
[13] J. B Skipper, C. W. Craighead, T. A. Byrd, R. K. Rainer, Int. J. of Physical Distribution & Logistics Management. 38 (2008) 39 - 56
[14] S. Serdarasan, Computers & Industrial Engineering. 66 (2013) 533–540
[15] M. Paliwal, U. A. Kuma, Expert Systems with Applications. 36 (2009) 2–17
[16] R. Carbonneau, K. Laframboise, R. Vahidov, European J. of Operational Research. 184 (2008) 1140–1154
[17] M. Tkác, R. Verner, Applied Soft Computing. 38 (2016) 788–804.
[18] T. Efendigil, S. Önüt, Computers & Industrial Engineering. 62 (2012) 554–569.
[19] K. Bertels, J. M Jacques, L. Neuberg, L. Gatot, European J. of Operational Research. 115 (1998) 608-615.
[20] T. Y. Kim, K. J. Oh, I. Sohn, C. Hwang, Expert Systems with Applications. 26 (2004) 583–590.
[21] L. Rabelo, M. Helal, C. Lertpattarapong, Proceedings of the 2004 Winter Simulation Conference. 1136–1144.
[22] H. C. Chen, H. M. Wee, K. Wang, Y. Hsieh, Third International Conference on Natural Computation.
[22] C. Almeder, M Preusser, R. F. Hartl, OR Spectrum. 31(2009) 95–119.
[23] U. E. Kocamaz, H. Taskin, Yılmaz Uyaroğlu, Alper Göksu. Computer & Industrial Engineering. 102 (2016) 476-487
[24] D. Peidro, J. Mula, R. Poler, F. C. Lario, The Int. J. of Advanced Manufacturing Technology. 43(2009) 400–420.