ANALYSING PERFORMANCE OF SUPPLY CHAIN MANAGEMENT ACTIVITIES USING ARTIFICIAL NEURAL NETWORKS

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Abstract

Performance measurement is critical in supply chain management activities since it creates understanding and leads to competitive results. In order to measure supply chain management performance, a comprehensive study of measurement is necessary. In this study, the objective is to identify the most effective supply chain management activity or the combination of activities that effect the performance of Turkish firms. For this purpose, artificial neural networks are used to measure and analyze the performance of supply chain management activities. The potential supply chain management activities are used as inputs and the firms' supply chain management performance level as the output of an artificial neural network model. The related data are gathered from the conducted survey.

Keywords: Supply chain management; Artificial neural networks
Topic Area: B6 Integrated Supply Chain Management

1. Introduction

Performance measurement is critical in supply chain management (SCM) activities. However there is little agreement in the literature about what should be measured. Additionally, although there are some performance improvement strategies that can be implemented by organizations; there is no complete consensus about the strategies and/or activities that will be most appropriate in improving the performance of the company's supply chain management activities.

Generally, performance measurement research focuses on analyzing performance measurement systems that are already in use. They categorize performance measures, then study the measures within a category, and build rules of thumb or frameworks by which performance measurement systems can be developed for various types of systems. In fact, to decide which of the supply chain management activities would lead to the best supply chain performance, is a critical question for managers in order to improve the supply chain performance of the organizations. In this sense, the objective of this study is to identify the most effective supply chain management activity or the combination of activities that effect the SCM performance of Turkish firms.

In this study, artificial neural networks are used to measure and analyze the performance of supply chain management activities. Figure 1 illustrates the proposed approach in detail.

The remainder of this paper is organized as follows. In the second section, the importance of performance measurement in supply chain management activities is described in detail. Then, the artificial neural networks approach that is proposed for evaluating the performance of supply chain management activities is explained. The fourth section shows the application to measure and analyze the performance of supply chain management activities. Finally, conclusions and further suggestions are provided. The essence of te methodology isbased on the one used by Montagno et al (2002) for identifying organizational improvement strategies and is adopted to the identification of the supply chain strategies that have the highest impact in the overall supply chain performance of the firms. The framework of the methodology used is given in Figure 1

Conduct the survey

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Use the results gathered from the survey as the data of the ANN

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Use the ANN to get the best MSE and RMSE values

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Determine the importance of the inputs by the help of weights of the ANN

Figure 1 Flowchart of the methodology used in the study

2. Performance measurement in supply chain management activities

Supply chain management is the integration of key business processes from the end user through original suppliers that provide products, services, and information that add value for customers. SCM initiates integration and management of multiple key business processes within and beyond the organizational boundaries. For improved competitiveness, increased organizational effectiveness and profitability; effective SCM activities are necessary (Lai et al., 2002).

Better performance measurement in SCM activities plays a key role in these activities and is essential to combining cross-functional agility with functional excellence(Fawcett and Cooper, 1998). Van Hoek (2001) emprically shows that a comprehensive performance measurement supports the development of innovative supply chain formats.

Traditional supply chain performance measurement systems have mainly focused on operational measures and have been designed to capture information regarding 5 types of performance generally regarded as essential to accomplishing the organization’s supply chain/distribution activities, which are: asset management, cost, customer service, productivity and supply chain quality. However, by the 1990s, many competetive and environmental developments have emerged and a need for a new set of more strategic measures has appeared. Those traditional measures have no more been capable of providing the insight needed to manage supply chain operations in a dynamic and competetive global matketplace (Gilmour, 1999; Fawcett&Cooper, 1998). Moreover, the shift to SCM has brought two implications for logistical performance: in this case, performance measurement must recognize the particular role of an organization in the supply chain (SC) and must be focused on the performance of the entire SC rather than that of individual members (Chow et al., 1994), since “SCM involves expanding the integrated supply chain concept beyond the corporate borders of the firm to include the supply chain operations of vendors and customers” (La Londe and Masters, 1994). In their research about improving the efficiency and effectiveness of SC, thus, Li and O’Brien (1999) analyse the performance of SC at two levels, namely the chain and the operations level. Gunesakaran et al.(2003) indicate in their conceptual work that “for effective performance measurement and improvement, measurement goals must represent organizational goals and metrics selected should reflect a balance between financial and non-financial measures that can be related to strategic, tactical and operational levels of decision making and control” and using the results of an emprical study after a review of the current literature, they develope a framework for SCM performance measurement. Additionally, Bowersox et al. (1995) suggest to maintain a balance between internally focused and externally oriented measures. Otto and Kotzab (2003) define another framework with six unique sets of metrics for measuring the effectiveness of SCM and argue theoretically that different approaches to SCM lead to different awareness of what should be measured to assess performance. Shmitz and Platz (2003) propose a framework for intra-organizational performance measurement, which is based on a literature review, as well as analysing the functions of supplier supply chain performance measurement emprically. Lohman et al. (2003) represent a new SC performance measurement experiment for the literature which include the clustering, the hierarchical levels and the graphical formats.

In the literature, the concept of supply chain or SC processes performance assessment has been applied in different extents, depending on the aim of the studies. While many papers (e.g., Stank&Traichal, 1998; Stock et al. 1998) have regarded logistical performance from the manufacturing firms' point of view, some other (e.g.Donselaar et al.,1998) have focused on it from the distributors' point of view. The idea is that different organizations or industries should include metrics and weightings as appropriate to their own needs and also that performance measures need to reflect the objectives of supply chain management (Stainer, 1997). For the purposes of their research on integrated supply chain, Daugherty et al. (1996) have selected six supply chain performance measures, each reflecting a typical supply chain goal. Stock et al. (2000) have used two types of performance measures in order to examine the fit between an organization's enterprise supply chain integration capabilities and its SC structure: operational measures for evaluating internal manufacturing and supply chain processes within the firm and financial measures to indicate the assessment of the firm by factors outside of the firm's boundaries. Persson and Olhager (2002) have prefered to evaluate the alternative SC designs with respect to costs, lead-times and quality, which they believe form a mix of measures representing resources, output and flexibility. Markham and Westbrook (2001) included "speed of product development" and "number of new products developed" among the 19 performance indicators they use for evaluating different SCM strategies. Wilding and Newton (1996) emphasized the importance of time focusing in performance measurement. In fact, there is little aggrement as to exactly what should be measured (Chow et al. 1994; Lohman et al., 2003). So, the objective is to be, finding a set of measures which collectively capture most of the performance dimensions.

Among a number of SC performance frameworks, the supply chain operations reference model (SCOR) developed by the Supply Chain Council(www.supplychain.org) provides a useful one that considers the performance requirements of member firms in a supply chain (Lai et al., 2002). The model is designed and maintained to support supply chains of various complexities and across multiple industries. It is focused on three process levels and organized around the five primary management processes of plan, source, make, deliver and return.

3. Artificial neural networks

Artificial neural networks represent a collection of mathematical models that provide an alternative to conventional statistical prediction techniques. While other popular techniques, such as linear regression, identify the linear trends in data, neural networks are particularly useful in recognizing patterns in data. The literature (Swanson White, 1997; Boznar et al., 1993; Hwarng and Ang, 2001) suggests the potential advantages of ANN over statistical methods. One such advantage is better performance of ANN when extreme values exist. Another advantage of ANN is that the estimation of an ANN can be automated, while the regression and ARIMA models must be re-estimated periodically whenever new data arrives. Especially when it is necessary to work with nonlinear data, ANN gives better results than the traditional methods (Gately, 1996). In fact, one of the primary applications of ANN is in understanding complex nonlinear mapping (Hruschka, 1993). It has been proved that a network with only one hidden layer is enough to approximate any continuous function. Therefore, ANN might represent a viable alternative to econometric techniques. Besides, ANN performs better in terms of mean absolute error (MAE) and mean absolute percent error (MAPE) (Hwarng and Ang, 2001). Moreover, neural networks are also better in capturing turning points. This is why in this study ANN is proposed for determining the importance of the major driving forces via estimation.

The basic model of ANN techniques consists of computational units, which emulate the functions of a nucleus in a human brain. The unit receives a weighted sum of all its inputs and computes its own output value by a transformation or output function. The output value is then propagated to many other units via connections between units. In general, the output function is a linear function- a threshold function in which a unit becomes active only when its net input exceeds the threshold of the unit, or a sigmoid function, which is a non-decreasing and differentiable function of the input. Computational units in an ANN model are hierarchically structured in layers. In the ANN literature, the process of computing appropriate weights is called “learning” or “training”. The learning process of ANN can be thought of as a reward and punishment mechanism (Hruschka, 1993). When the system reacts appropriately to an input, the related weights are strengthened. As a result, it will be possible to generate outputs, which are similar to those corresponding to the previously encountered inputs. Contrarily, when undesirable outputs are produced, the related weights are reduced. Therefore, the model will learn to give a different reaction when similar inputs occur. Thus, the system is motivated toward producing desirable results while the undesirable ones are “punished”.

Currently, there are many different learning algorithms, which work with different types of output function in various network architectures (Masters, 1993). One of the most popular neural network paradigms, which are also used in this study, is the feed-forward neural network and the associated back-propagation training algorithm. The back-propagation algorithm consists of two steps: the forward pass and the reverse pass (Chiang et al., 1996; Tang and Fishwick, 1993). In the forward pass the input unit simply passes on the input vector x. The units in the hidden layer and output layer are processing units. Each processing unit has an activation function, which is commonly a sigmoid function.

$$f(x) = \frac{1}{1+e^{-x}}$$

The net input to a processing unit j is given by

$$net_j = \sum_i w_{ij} x_i + \theta_j$$

where x_i’s are the outputs from the previous layer, w_{ij} is the weight of the link connecting unit i to unit j, and θ_j the bias, which determines the location of the sigmoid function on the x-axis.

A feed forward neural net works by training the network with known examples. A random sample (x_p, y_p) is drawn from the training set $\{(x_p, y_p) \mid p=1,2,..,P\}$ and x_p is fed into the network through the input layer. The network computes an output vector o_p based on the hidden layer output. o_p is compared against the training target y_p. A performance criterion function is defined based on the difference between o_p and y_p. A commonly used criterion function is the sum of squared error function:

$$F = \sum_p F_P = \frac{1}{2} \sum_p \sum_k (y_{pk} - o_{pk})^2$$

where p is the index for the pattern (example) and k is the index for output units.

The error computed from the output layer is backpropagated through the network, and weights (w_{ij}) are modified according to their contribution to the error function.

$$\Delta w_{ij} = -\eta \frac{\partial F}{\partial w_{ij}}$$

where η is called learning rate, which determines the step size of the weight updating.These forward and reverse passes are continually executed for each learning pair of the learning set.

Since the basic backpropagation learning algorithm is too slow for many practical problems, high performance numerical optimization techniques have been applied to provide its faster convergence. One of those is the Marquardt-Levenberg modification to the backpropagation algorithm, which is described by Hagan&Menhaj (1994). While basic backpropagation is a steepest descent algorithm, this algorithm includes an approximation to the Newton's method. The update formula,

$$\underline{x}_{k+1} = \underline{x}_k - \left[J^T(\underline{x}_k)J(\underline{x}_k) + \mu I\right]^{-1} J^T(\underline{x}_k)\underline{e}(\underline{x}_k)$$

is used where $\underline{e}(\underline{x})$ is the vector of network errors and $J(\underline{x})$ is the Jacobian matrix. The Jacobian is computed by a simple modification to the standard backpropagation algorithm. When the parameter μ is large, the algorithm becomes steepest descent and for small μ values it becomes Gauss-Newton. Thus, when a step result with an increased performance function, μ is multiplied by some factor (β), while after a step reducing the performance function, μ is divided by β. It has been found that the Marquardt algorithm is quite efficient in training networks with up to a few hundred weights.

The aim of training a neural network is not only minimizing the sum of squared errors for the training data set, but also providing a good generalization ability for the network. Regularization and early stopping are two methods to overcome this generalization problem. It is shown for linear networks that under optimal parameter settings, these two methods have equivalante generalization performances (Hagiwara, 2002). However, using regularization seems to be more suitable when the size of the data set is small -as in our case-, since it does not require an additional validation data set.

Generally, the aim of the training is to minimize sum of squared errors. Regularization adds an additional term to this objective function, so it becomes $\beta E_D + \alpha E_W$, where E_D is the sum of squared errors, E_W is the sum of squared weights and β, α are the parameters. The Bayesian technique is an approach for the optimization of these objective function parameters. Foresee&Hagan (1997) propose that if the Marquardt-Levenberg algorithm is used to achieve Bayesian optimization, the additional computation for optimization of the regularization is minimal. In this paper, their approximation to the Bayesian regularization, which is in combination with the Marquardt algorithm, is used. With the use of this algorithm, whatever the number of total parameters (weights and biases) is, the effective number of parameters remain approximately the same; so does the E_D and E_W function values.

In multilayer neural networks in order to determine the characteristic of each input neuron and the strength of the connection between input X_i and output O_i, different weight measurement techniques can be used. One such a measure is proposed by Yoon et al. (1993).

$$RS_{ji} = \frac{\sum_{k=0}^{n}(W_{ki} * U_{jk})}{\sum_{i=0}^{m}\left|\left(\sum_{k=0}^{n}(W_{ki} * U_{jk}\right)\right|}$$

In this formula, RS_{ji} is the strength of the connection between input i and output j. W_{ki} is the weight between the hidden neuron k and input neuron i, while U_{jk} is the weight between output neuron j and hidden neuron k. This statistic, in fact, is the ratio of strength between input i and output j to the total strength of all input-output neurons. The absolute value in the denominator is used to eliminate the negative relations between input-output neurons.

The absolute value of the weights connecting the input neurons to the hidden neurons is another measurement that can be used. In this measurement, the inputs that are connected to hidden units with weights about zero are expected to have little impact on outputs. In some of the ANN software this measurement is used after training and the sum of weights of each input is determined in order to rank the inputs according to their strength (Gately, 1996).

The third measure is based on sensitivity analysis proposed by Masters (1993). The importance of the input can be put forward by the error ratio determined from the training data set by fixing one of the inputs and analyzing its effect on the error ratio. That is, if an important change is not determined, the related input is put backwards in the resulting importance ranking. If the analyzed input value is set to zero, its impact on the error of the training set can be analyzed easily.

In this study all of the three methods mentioned above are used for estimating the importance of the inputs of the ANN.

4. Survey results

This study aims to investigate the most important SCM activities that play key roles in the firms' overall SCM performance. As it is described in the above section, by examining the weights of the neural networks, one can easily determine not only the relevant supply chain management activities but also the order of their importance. In order to find the input data of the artificial neural network, in the initial step, a survey is conducted with the top 250 firms, member of the Istanbul Chamber of Commerce. In this research data were collected through a structured 7-page mail survey. A pre-test was conducted with 10 firms to avoid inapplicable questions and ambiguous wording. The questionnaire are sent by mail and e-mail. The mailing was done in two stages. All non-respondents to the first stage were sent a second survey by fax and were requested to respond either by fax or by e-mail. Some of the firms were directly visited and the responses were obtained through depth-interview. As a result, a total of 55 questionnaires were obtained, representing a 22% response rate.

The questionnaire was designed to analyze the most important strategy (ies)n that should be used by an organisation in order to have a successful supply chain and it was directedto the manager of the orginisation responsible from the supply chain activities.

Three main types of variables were included to analyze the impact of supply chain strategies to the success of the organization.

a) **Profile-based variables**: Industry in which the firm operates, duration of operation, number of employees, existence of a foreign partnership, gross revenue, sector in which the firm operates, the basic markets that is served (foreign, national or both), the existence of a foreign partnership, the number of blue- collared and while- collared workers.

Nominal and ratio scaled open-ended questions are used in order to measure majority of the profile-based variables in the questionnaire. Perceived position of supply chain activities is also measured by a multiple-choice question that investigates the relative position of supply chain activities with respect to production, marketing, purchasing, research and development, human resource management and other activities within the organization..

b) **Variables related to supply chain strategies**: In this second group of variables, the supply chain strategies adopted by the surveyed firm are analysed in five perspectives; namely people, process, technology, business strategy and measurement. Five-scale interval is used for this purpose (1. I do not definitely agree, ..5. I definitely agree)

The questions about *staff* investigate the knowledge level of the staff about the meaning of a supply chain, their awareness about their importance as a key part of it, as well as its importance in the success of their organization. The manager is also asked whether the staff is composed of the right people to drive supply chain success.

The questions about the *process* analyse the ability of the organization to map the entire supply chain, whther the business processes are supply chain focused and designed to encourage collaboration and finally whether supply chain activities are done in a way integrated to sales and operations planning processes.

From the *technology perspective*, the manager is asked whther the current systems are used to provide the decision support required to optimize the supply chain, the degree to which the technology facilitate collaboration with customers and supplers.

The questions about *business strategy* investigate the existence of a supply chain vision in the company, the interaction and suitability of the supply chain strategy to the overall business strategy, the role of CEO in the support of SCM activities.

Finally the *measurement systems* of the firm is also analysed by the questions about the availability of the measurement system to measure the supply chain today, the ability to quantify the gap between the current situation of the company and where it needs to be, and the ability to know the potential impact of supply chain success of shareholder value.

c) **Variables related to the success level of the company based on performance indicators in different areas.**

The success level of the company is analysed from the customer as well internal operations-based performance indicators. A five-scale interval (1: very unsucessful..5.very successful) is used for this purpose.

Key performance indicators for supply chain management are specified according to the SCOR (Supply chain operations reference) model of the Supply Chain Council(www.supplychain.org). They can be grouped under delivery performance, supply chain responsiveness, assets-inventory and costs.

The customer-focused success is investigated based on *reliability* (delivery performance, fill rate and perfect order fulfillment), *responsiveness (*order fulfillment lead time) and *flexibility* (supply chain response time, production flexibility)

The success in terms of internal operations is analysed from the *cost perspective* (total supply chain management cost, cost of goods sold, value-added productivity, warranty cost or returns processing cost) as well as assets perspective (cash-to-cash cycle time, inventory days of supply and asset turns).

The majority of surveyed companies are middle or large size companies with a gross revenue greater than $50 million (53%) and with the number of employee higher than 500 (77.2%).The majority are in the food (25%) and textile sector (32%) and do business both in national and international markets(70%) (see Table 1)

Table 1 General and Organizational Characteristics of the Firms

Operating Area	(%)	Number of Employees	(%)
Food/Beverage	25	-500	37
Clothing /Textile.	32	501-1000	43
Durable consumer goods (automobile, white appliances)	17	1001+	34.2
		Market structure	**(%)**
Electronics/Communication	10	Priority is given to international markets	22
Basic Industry (iron/steel, paper, mine, plastics etc)	14	International and national markets equally served	35
Other	2	Priority is given to local markets	35
		Only international markets	5
		Only national markets	4
		Gross income	**(%)**
		<50	47
		50-100	29
		100+	24

The surveyed firms especially emphasizes the importance of production (91.3%) in the success of a company, followed by marketing(86%) and finance(82%). Supply chain is at the fourth level (78%) and therefore its importance is not yet clearly understood by the respondents firms.Themajority believe that their most dominant supply chain strategy is to adapt the supply chain activities to the changing conditions (36%) and to integrate all the supply chain activities rather than treating them individually (25%)

5. The analysis of the performance of SCM activities using ANN

In order to specify the importance of different supply chain management strategies, the average values of the 17 variables cited in B category revealed from the survey results are used as inputs and the firms' supply chain management performance level. A was mentioned before these activities are grouped under five main categories; namely, staff, process, technology, business strategy and measurement. The overall average value of all the variables in C category is accepted to represent the overall success level of the company andi thus, is accepted to be the output of an artificial neural network model.

These activities can be grouped under five major categories as employees, processes, technologies, strategies and measurement. The network's single output representing the overall supply chain management performance of the firm is the arithmetic average of key performance indicators gathered from the survey results.

As it can be seen from Figure 2, the ANN architecture used in this study has only one hidden layer. As generally prefered for feedforward networks, a sigmoid function, hyperbolic tangent, is used for the hidden layer and a linear transfer function is used for the output layer. Among the 55 data at hand, 10 were seperated randomly as the testing data to compare the generalization performances of different networks and the remaining 45 were used for training. In order to determine the appropriate number of hidden neurons, networks were tried with the number of neurons beginning from 2 to 12. Every network was trained several times starting with different initial weights to guarantee robust performance. Training is continued until convergence is achieved, that is the sum squared errors, the sum squared wights and the effective number of parameters became constant.

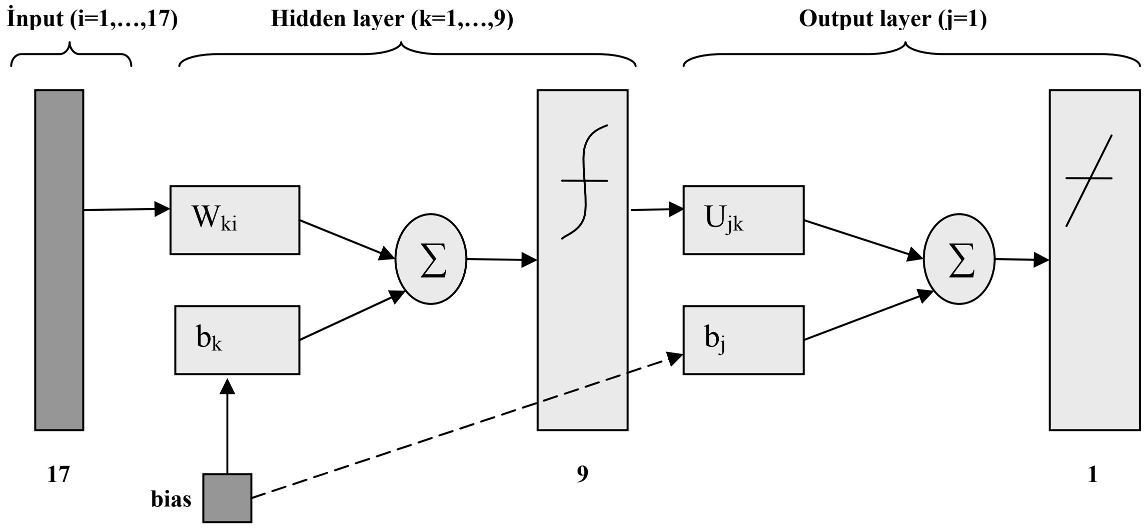

Figure 2 The ANN architecture

As expected from the special training algorithm used, the performances of the networks were close. However, the network with 9 hidden neurons gave the best acceptable performance value for both the training and the test data sets. The mean square error (MSE) and root mean square error (RMSE) values for train and test sets are (0.04; 0.2) and (0.12; 0.35) respectively.

In order to determine the characteristic of each input neuron and the strength of the connection between input X_i and output O_i, each of the three weight measurement approaches is used and the average of all the three measures is taken. Only Yoon's measurement is slightly changed by taking the square of both the numerator and the denominator in order to make it more effective and thus making the sum of the weight equal to 1. The results are given in Table 2.

Figure 3, which is based on the average weights, shows that the most important logistics activities that influence the performance of the firms is (2) the ability of the staff to see itself as a key part of the supply chain. This is followed by (12), the existence of a clear supply chain managwment vision and the suitability of the supply chain strategy to the overall business strategy of the company.

However, the surveyed firms do not believe in the importance of the CEO's being the biggest advocate of SCM within the organization as well as the ability of the company to measure the supply chain.

6. Conclusion and further suggestions

This study aims to provide a tool for the selection of the best supply chain management strategy(ies) to improve the supply chain performance level of the company. It contributes to an understanding of the complexities of the supply chain management decision process. Artificial neural network is used as an aid to decision making. The inputs of the artificial neural network are taken to be the average value of each of 17 supply chain strategies revealed from the survey.

Analyzing the weights of the related artificial neural network helps us to specify the strategies that have the greatest impact on the supply chain management performance level. Choosing one supply chain strategy over another is a difficult task for supply chain managers This study does not claim to prescribe one strategy over the other, it offers the current picture of the Turkish firms and help them to examine the success level of them and the basic strategies that contributed to their success.

Table 2 The Ranking of the Supply Chain Management Activities

	Logistics Activities	Sensitivity Analysis	Absolute Value Measurement	Yoon's Measurement	Average Value
1	Our staff know what a supply chain is	0,057054456	0,029694655	0,069455782	0,0520683
2	All the staff see itself as a key part of the process	0,045935501	0,151294361	0,162734651	0,1199882
3	Our people realize the importance of supply chain success	0,057572001	0,051895329	0,010098531	0,0398553
4	In our organization, right people are empowered and goaled to drive supply chain success	0,066921812	0,026451014	0,051097484	0,0481568
5	We can map our organization end to end supply chain	0,062861666	0,072546986	0,008786513	0,0480651
6	Our business processes are supply chain focused and designed to encourage collaboration	0,052239522	0,042769055	0,046169114	0,0470592
7	We are driving our business with a sales and operations planning process	0,058281604	0,038373016	0,061786168	0,0528136
8	We use our current systems to provide the decision support required to optimize the supply chain	0,052391598	0,04975467	0,114584419	0,0722436
9	Our technology facilitate collaboration with customers	0,064243578	0,063460889	0,084887101	0,0708639
10	Our technology facilitate collaboration with suppliers	0,062427094	0,047690116	0,025120369	0,0450792
11	Our supply chain software are suitable to our supply chain activities	0,061430253	0,045248903	0,04230909	0,0496627
12	The company has a supply chain vision	0,055417397	0,15184532	0,109453244	0,105572
13	Supply chain strategy talk to the overall business strategy	0,054743849	0,069604855	0,114166357	0,079505
14	Our CEO is the biggest advocate of SCM within the organization	0,059941944	0,049027853	0,005770833	0,0382469
15	W e can measure our supply chain today	0,062686875	0,020718206	0,023029059	0,035478
16	We can quantify the gap between where we are now and where we need to be	0,066172333	0,033697665	0,059912046	0,0532607
17	We know the potential impact of supply chain success on shareholder value	0,059678519	0,055927108	0,010639237	0,0420816

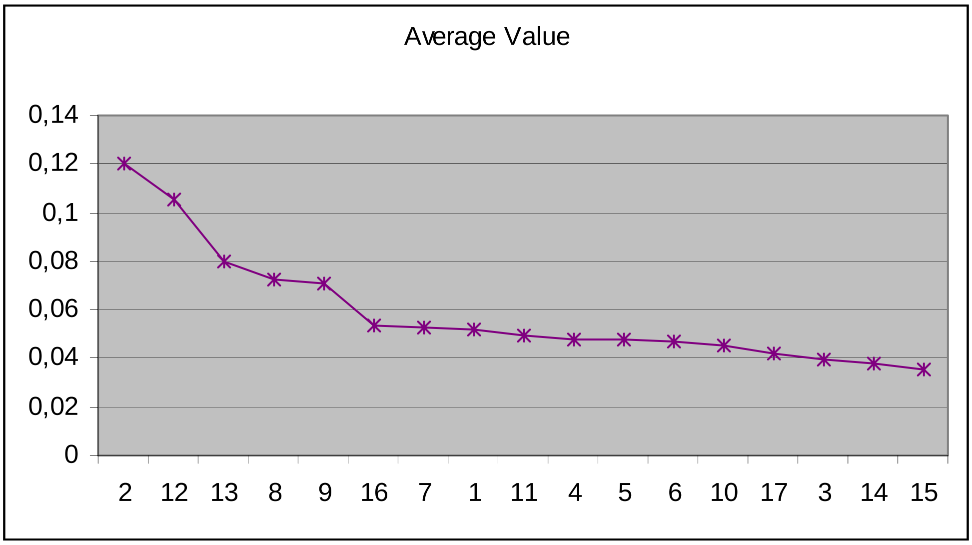

Figure 3 The Importance Ranking of the Inputs

Table 2 and Figure 3 provide some insight for managers into making choices about where they should spend resources first. The strategies having the highest weight appear to be the approaches that have the highest impact on the overall performance of the firms when used independently. In the surveyed firms the basic factors contributing to the overall peroformance of the supply chain activities is the awareness of the employees that they are a key part of the process, the availability of a well defined supply chain vise compatibility between the supply chain and overall business strategy. However, in the surveyed firms the importance of an accurate measurement as well as of human resource systems are very low in the overall success of the supply chain activities. The main reason of these low weights may be due to the fact that those firms accept their contribution to the success when accompanied by the use of other approaches. They may also require a long development period and depend on the realization of other changes.

The main limitation of this research is due to the limited number of returned questionnaires. In order to increase the validity of the results, the survey size should be increased. This will also permit to analyse the differences among the sectors in terms of the importance that they attach to the strategies and detailed multivariate analysis such as factor analysis and cluster analysis can also be applied.

References

Bowersox, D.J., Daugherty, P.J., 1995. Supply Chain Paradigms: The Impact of Information Technology, *Journal of Business Supply Chain*, 16(1), 65-75.

Boznar, M., Lesjak, M., Mlakar, P., 1993. A Neural Network-based Method for Short-term Predictions of Ambient SO2 Concentrations in Highly Polluted Industrial Areas of Complex Terrain. Atmospheric Environment, B Urban atmosphere, 27B, 221-230.

Chiang, W-C, Urban, T.L., Baldridge, G.W., 1996. A Neural Network Approach to Mutual Fund Net Asset Value Forecasting, Omega Int. J. Mgmt. Sci., 24/2, 205-215.

Chow, G., Heaver, T. D., Henriksson, L. E., 1994. Logistics Performance: Definition and Measurement, Int. Journal of Physical Distribution & Logistics Management, 24 (1) 17-28.

Daugherty, P.J., Ellinger, A.E., and Gustin, C.M., 1996. Integrated logistics: achieving logistics performance improvements, Supply Chain Management, 1 (3) 25–33.

Fawcett, S.E., Cooper, M.B., 1998. Logistics Performance Measurement and Customer Success, Industrial Marketing Management, 27, pp. 341-357.

Foresee, F. D., and Hagan, M. T., 1997. Gauss-Newton approximation to Bayesian regularization, Proceedings of the 1997 International Joint Conference on Neural Networks.

Gately, 1996. Neural Networks for Financial Forecasting. John Wiley & Sons, Inc, USA.

Gilmour, P., 1999. Benchmarking supply chain operations, International Journal of Physical Distribution & Logistics Management, 5 (4) 259-266.

Gunasekaran, A., Patel, C., McGaughey, R.E., 2003. A framework for supply chain performance measurement, International Journal of Production Economics, 87 (3) 333-347.

Hagan, M.T., and Menhaj, M., 1994. Training feedforward networks with the Marquardt algorithm, IEEE Transactions on Neural Networks, 5 (6) 989–993.

Hagiwara, K., 2002. Regularization learning, early stopping and biased estimator, Neurocomputing, 48, 937-955.

Hruschka, H., 1993. Determining Market Response Functions by Neural Network Modeling: A Comparison to Econometric Techniques, European Journal of Operational Research, 66, 27-35.

Hwarng, H.B., Ang, H.T., 2001. A Simple Neural Network For ARMA (p,q) Time Series. Omega, 29, 319-333

La Londe, B. J., and Masters, J. M., 1994. Emerging logistics strategies: Blueprints for the next century, International Journal of Physical Distribution & Logistics Management, 24 (7) 35-47.

Lai, K., Ngai, E.W.T., Cheng, T.C.E., 2002. Measures for evaluating supply chain performance in transport logistics, Transportation Research, Part E 38, 439–456.

Li, D., and O'Brien, C., 1999. Integrated decision modelling of supply chain efficiency, International Journal of Production Economics, 59, 147–157.

Lohman, C., Fortuin, L., Wouters, M., 2003. Designing a performance measurement system: A case study, European Journal of Operational Research, Article In Press.

Markham, T. F., and Westbrook, R., 2001. Arcs of integration: an international study of supply chain strategies, Journal of Operations Management, 19, 185–200.

Masters, 1993. Practical Neural Network Recipes in C++. Academic Press, USA

Montagno, R., Sexton, R.S., Smith, B.N., 2002. Using Neural Networks for Identifying Organisational Improvement Strategies, European Journal of Operational Research, 142, 382-395

Otto, A., and Kotzab H., 2003. Does supply chain management really pay? Six perspectives to measure the performance of managing a supply chain, European Journal of Operational Research, 144, 306–320.

Persson, F., Olhager, J., 2002. Performance simulation of supply chain designs, International Journal of Production Economics, 77, 231-245.

Schmitz, J., Platts, K.W., 2003. Supplier logistics performance measurement: Indications from a study in the automotive industry, International Journal of Production Economics, Article In Press.

Stainer, A., 1997. Logistics – a productivity and performance perspective, Supply Chain Management, 2 (2) 53–62.

Stank, T. P., and Traichal, P. A., 1998. Logistics strategy, Organizational Design, and Performance in a cross-border environment, Logistics and Transportation Review, 34 (1) 75-86.

Stock, G.N., Greis, N.P., Kasarda, J.D., 1998. Logistics, strategy and structure: A conceptual framework, International Journal of Operations & Production Management, 18 (1) 37-52.

Stock, G. N., Greis, N. P., Kasarda, J. D., 2000. Enterprise logistics and supply chain structure: the role of fit, Journal of Operations Management, 18, 531–547.

Swanson, N.R., and White, H., 1997. Forecasting economic time series using flexible versus fixed specification and linear versus nonlinear econometric models. International Journal of Forecasting, 13 (4) 439-461

Tang and Fishwick, 1993. Feedforward Neural Nets as Models for Time Series Forecasting. ORSA Journal on Computing, 5 (4) 374-385.

Van Donselaar, K., Kokke, K., and Allessie, M., 1998. Performance measurement in the transportation and distribution sector, International Journal of Physical Distribution & Logistics Management, 28 (6) 434-450.

Van Hoek, R.I., 2001. The contribution of performance measurement to the expansion of third party logistics alliances in the supply chain, International Journal of Operations & Production Management, 21 (1/2) 15-29.

Wilding, R.D., and Newton, J.M., 1996. Enabling time-based strategy through logistics – using time to competitive advantage, Logistics Information Management, 9 (1) 32–38.

Yoon, Y., Swales, G., Margavio, T.M., 1993. A Comparison of Discriminant Analysis versus Artificial Neural Networks. Journal of Operational Research, 44 (1) 51-60.

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