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A hybrid approach to supplier performance evaluation using artificial neural network: a case study in automobile industry

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Abstract

For many years, purchasing and supplier performance evaluation have been discussed in both academic and industrial circles to improve buyer-supplier relationship. In this study, a novel model is presented to evaluate supplier performance according to different purchasing classes. In the proposed method, clustering analysis is applied to develop purchasing portfolio model using available data in the organizational Information System. This method helps purchasing managers and analyzers to reduce model development time and to classify numerous purchasing items in a portfolio matrix. In this paper, Neural Networks are used to develop a purchasing classification model capable of classifying purchasing items according to different features. Moreover, a new supplier evaluation model based on different purchasing classes is developed using Neural Networks. The proposed hybrid method to develop purchasing portfolio and supplier evaluation is applicable in large scale manufacturing organizations which need to manage numerous purchasing items. The proposed model is implemented in an automaker purchasing department with a relatively vast supply chain and the results are presented.

Keywords: Supplier performance evaluation, Purchasing portfolio model, Artificial neural network.

1. Introduction

Supplier evaluation process is one of the most important processes in the field of Supply Chain Management (SCM), which can influence overall performance of the companies. The selection of appropriate suppliers and effective supplier relationship management are the key

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factors in increasing the competitiveness of firms (Ghodyspour and O'Brien, 2001). Nowadays, the establishment of a long term relationship with suppliers is recognized as an effective approach to Supplier Relationship Management (SRM). Like every long term human relationships, in which the relations are evaluated continuously and are compared to the ideals, organizations need also to evaluate long term relationships with their suppliers in order to make appropriate decisions in right time.

In a long term buyer-supplier relationship, purchasing managers need to perform periodic supplier performance evaluation in order to make appropriate decisions about the continuation of the relationship (Aksoy and Öztürk, 2011). In this regards, many different methods are used to implement supplier evaluation and classification systems. Recently, Artificial Neural Networks (ANN) are considered by researchers for supplier performance evaluation, as they does not require formulating the decision-making process explicitly and can cope better with complexity and uncertainty than traditional methods (Aksoy and Öztürk, 2011) (Temur, Özdemir, and Kaya, 2009).

On the other hand, purchasing is a key strategic activity to achieve high quality, high variety, low cost and fast delivery of the end-product (Lee and Drake, 2010, Scotta et al. 2014). In recent years the purchasing managers are suggested to categorize their suppliers using portfolio models and adopting the different appropriate strategies to each category by the introduced professional purchasing processes. Kraljic (1983) proposed a purchasing portfolio model, which classifies purchasing items according to their relative contribution towards supply risk and profit impact for the firm (Padhi, Wagner, & Aggarwal, 2012). According to the widespread use of professional purchasing processes, it seems necessary to develop the supplier performance evaluation model based on the principles of purchasing portfolio models. In other words, not only different strategies are needed to different purchasing classes, but also these classes should be considered in supplier performance evaluation process.

In large-scale organizations, suppliers' performance cannot be evaluated only according to the judgment of managers, because they buy numerous commodities, and classify purchasing items according to the portfolio purchasing model, which is a huge job. Therefore, it seems necessary to develop an appropriate purchasing classification and supplier performance evaluation system for large-scale organizations to simulate the managers' judgments. So, the main objective of this paper is to present a hybrid model to classify purchasing items, and to evaluate supplier performance using ANN. This paper is organized as follows: In section 2, a comprehensive review in the field of purchasing portfolio models and supplier performance evaluation models including various criteria and methods is provided. In section 3, the proposed hybrid model for purchasing classification and supplier performance evaluation is presented. In section 4, the proposed model is implemented in an automaker supply chain and practical results are provided. In section 5, the conclusion and further research directions are presented.

2. Literature review

The buyer-supplier relationship in SCM context is investigated in various recent studies. Mostly, the main objective of these studies is to evaluate suppliers based on specific criteria and select the best suppliers base on a variety of multi-attribute decision-making techniques (Rezaei and Ortt, 2011, Sarkis and Dhavalel 2014, Scotta et al. 2014). Two important processes in buyer-supplier relationship, which are discussed here, are purchasing classification and supplier performance evaluation.

2.1. Purchasing classification

In general, two different approaches are used for purchasing classification. Some researchers classify the purchasing items and then classify indirectly the suppliers, according to the purchases. Kraljic (1983) as the pioneer in introducing purchasing portfolio model has used this approach. In his study a two dimensions consisting of profit impact and supply risk is applied to classify purchasing items into four classes: strategic, leverage, bottleneck and non-critical. Based on his work, Olsen and Ellram (1997), Gelderman and Van Weele (2003), Caniels and Gelderman (2005), Lee and Drake (2010) and Padhi, Wagner and Aggarwal (2012) have applied a similar approach in their studies with some changes in dimensions and assessment criteria.

Bensaou (1999) has proposed a portfolio model using two dimensions, buyer's specific investment and supplier's specific investment. In this study the supplier relationships are classified into four categories: strategic partnership, captive supplier, captive buyer and market exchange. Kaufman, Wood and Theyel (2000), Hallikas (2005) and Rezaei and Ortt (2011) have used similar approaches again with some changes in dimensions and assessment criteria.

In this research, The Kraljic Portfolio Matrix (KPM) is applied to classify purchasing items. Kraljic (1983) advised managers to protect their firms from damaging supply interruptions and to deal with continuous technological changes and economic growth (Caniels and Gelderman, 2005). The general idea of this research is to classify the purchasing items and dedicate appropriate purchasing strategies to each class in order to minimize the supply costs and enhance the purchasing performance (Padhi, Wagner and Aggarwal, 2012). The output of this model is a 2×2 matrix with two dimensions, profit impact and supply risk and four classes of classified items. Strategic items with high profit impact and high supply risk play the key role in organization success and a serious cooperation between buyer and supplier is needed to manage them. Leverage items with high profit impact and low supply risk, are important in the organization but they are managed comparatively easier. Bottleneck items with low profit impact and high supply risk, are not very important but they are time consuming and they take energy of managers to be handled. Non-critical items with low profit impact and low supply risk are less important and they are easy to be managed (Lee are Drake, 2010).

In the KPM, purchasing items are classified through two dimensions: profit impact and supply risk, although some researchers applied another names for dimensions such as strategic importance instead of profit impact. Each dimension is divided into two parts and then a 2×2 matrix is produced to classify purchasing items in four mentioned classes. Some measuring criteria are considered for each dimension to determine the position of each purchasing item on that dimension. Generally, vertical dimension is assessed by internal factors, which are measurable using the existing information in the organization and horizontal dimension is assessed by external factors, which are measured using information outside the organization.

Using questionnaire in order to obtain a total score in each dimension of the matrix and determining each item's position is the common method to produce the KPM. The organization experts' answers are used to weight the criteria and to find the score of each purchasing item. Finally the total score in each dimension for each item is calculated and then they are positioned in the KPM. Lee and Drake (2010) have used AHP to combine the measures and score the component value. They have named the vertical dimension as a component value and stated that AHP is an appropriate method because component value is relative rather than an absolute measure. In the AHP method, the relative importance of components is determined using pair-wise comparison with respect to the given criteria. Although they have just used 23 items in their implementation, in this way each expert was needed to do 3036 pair-wise comparisons which are boring and mistakes might be made in doing it.

Padhi, Wagner and Aggarwal (2012) have used Fuzzy AHP to weight the criteria and used Multi-Dimension Scaling (MDS) to map the purchasing items in the KPM. However, the matter of consuming valuable experts' time to score the factors still remains as a remarkable item.

2.2. Supplier performance evaluation

Dickson (1966) is the first researcher who issued the supplier evaluation problem based on multiple criteria. He analyzed interviews with 170 purchasing managers and concluded that among 23 different factors, quality, price and delivery are the most three important ones (Ha and Krishnan, 2008) (Wu, 2010). In order to draw out the key factors in a buyer decision making, Weber, Current and Benton (1991) have analyzed 74 available papers and figured out that the price is the first important factor and delivery and quality are consecutively the next two.

Utilization of a standard supplier evaluation system based on past experiences is vital to establish strong partnerships with suppliers (Choy, Lee, and Lau, 2005) (Temur, Özdemir and Kaya, 2009). The main goal of supplier selection is to minimize purchasing risk and costs by choosing the most appropriate suppliers and the main goal of supplier performance evaluation is to simplify decision making process on extending or discontinuing cooperation with a supplier. Despite the difference in their goals, supplier selection and supplier performance evaluation are similar in their processes. The major difference is in selecting suitable criteria for each process e.g. geographical distance might be a suitable criterion for the supplier selection process but it is not important in the supplier performance evaluation process. Although there are some common criteria such as price that might be a suitable criterion for both processes. Therefore, in order to have a more complete review and enrich the bases of this research, the supplier selection literature is also considered. Table 1 illustrates criteria and methods proposed in five distinct papers recently.

Using multi-dimensional information in the supplier evaluation process is important and well proceeded in both academic and practitioner's literature. According to literature, do not agree on a unique best way to evaluate suppliers, and so the organizations use a variety of different approaches in their evaluating processes (Ha and Krishnan, 2008). In practice, the final variables are usually selected by a team of experts/decision-makers (Rezaei and Ortt, 2011). Usually, the evaluation criteria are categorized into qualitative and quantitative variables. Then, a suitable method to each category is applied to obtain a total score (Ha and Krishnan, 2008) (Zeydan, Çolpan and Çobanoglu, 2011). Rezaei and Ortt (2011) presented another categorization for the criteria. In their proposed model, purchasing portfolio model is produced using two dimensions: supplier capabilities and supplier willingness.

Aksoy and Öztürk (2001) performed an extensive review of decision making methods to support both supplier selection and supplier performance evaluation processes. Several different methods such as categorical method, the weighted point method and the cost ratio method are introduced in the literature. Multi Criteria Decision Making (MCDM) techniques such as AHP and also, Mathematical Programming (MP) techniques such as DEA are used to develop supplier performance evaluation models. For more details see (Aksoy and Öztürk, 2011). Some researchers suggested to use fuzzy approaches to overcome the difficulty of measurement imprecision associated with qualitative factors (Sarkar and Mohapatra, 2006) (Araz, Ozfirat and Ozkarahan, 2007).

Table 1. Criteria and methods recently used for supplier evaluation

Author(s)	Criteria	Method
Ha and Krishnan (2008)	*Quantitative variables*: Quality system outcome (QSO), Claims (CL), Quality improvement (QI), Response to claims (RC), On-time delivery (OD), Internal audit (IA), Data administration (DA).	AHP + DEA + ANN(MLP,SOM)
	Qualitative variables: Production facilities (PF), Quality management intention (QMI), Organizational control (OC), Business plans (BP), Customer communication (CC).	
Temur et al. (2009)	Material quality (MQ), Distance (DIS), Discount on amount (DOA), Discount on cash (DOC), Annual revenue (AR), Payment term (PT), Delivery length (DL).	Artificial Neural Networks (MLP) + Discriminant Analysis
Wu (2010)	Quality personnel, Quality procedure, Concern for quality, Company history, Price-quality, Actual price, Financial ability, Technical performance, Delivery history, Technical assistance, Production capability, Manufacturing Equipment.	Stochastic DEA
Zeydan et al. (2011)	*Quantitative variables*: Defect Ratio (PPM), Warranty Cost Ratio (WAR), Quality Management (QM).	FAHP + Fuzzy TOPSIS + DEA
	Qualitative variables: New Project Management (C1), Supplier Management (C2), Quality & Environment Management, Production Process Management, Test & Inspection Management, Corrective & Preventive Management.	
Aksoy and Ozturk (2011)	Quality level, Percentage of rejected parts, Index of performance, Result of process audit, Performance of sample, Authority of non-supervised delivery.	Artificial Neural Networks (MLP)

A neural network based approach can deal with complexity and conflicts existing in selecting and evaluating supplier according to its two major characteristics, learning and recall; in addition, it does not require a formulation of the decision-making process explicitly (Aksoy and Öztürk, 2011). As compared to conventional models for decision support system, neural networks save a lot of time and money of system development (Zeydan, Çolpan and Çobanoglu, 2011). Here, a neural network based approach is used to develop both purchasing classification model and supplier performance evaluation model.

3. Proposed model for purchasing classification and supplier performance evaluation

The proposed model is a combination of Kraljic purchasing portfolio model and supplier performance evaluation model. The aim is to develop a supplier performance evaluation system, which is aligned with strategic procurement management. Figure 1 illustrates the conceptual model, proposed in this paper.

This model consists of two modules: Purchasing Classification Module (PCM) and Performance Evaluation Module (PEM). The features of each purchasing item are fed into the PCM as its inputs and then, PCM returns the number of the associated quadrant in Kraljic Portfolio Matrix (KPM) as the class of that item. This result and the features of each supplier altogether are fed into PEM and then, PEM returns the result of performance evaluation by means of estimating the evaluation function.

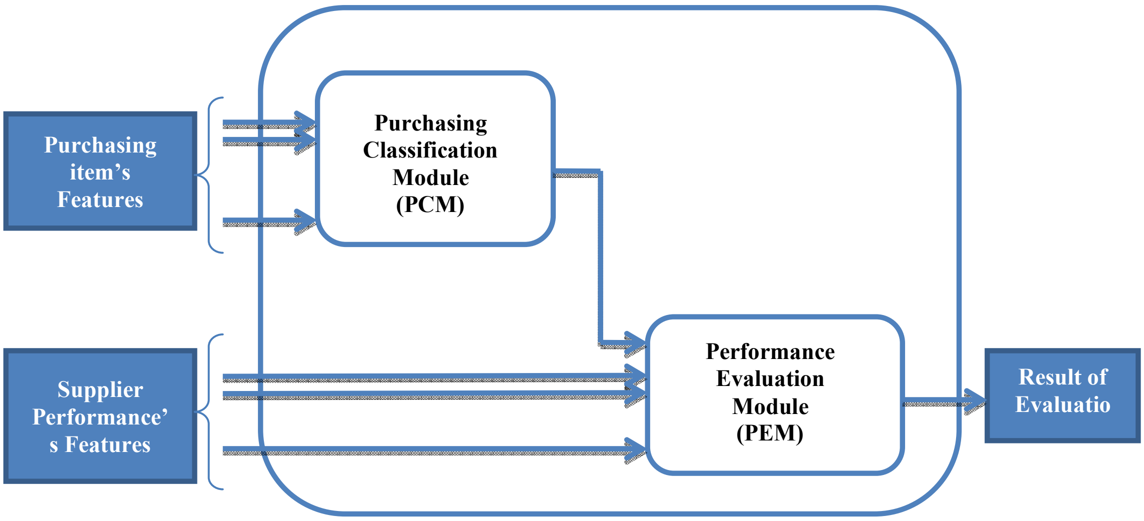

Figure 1. Conceptual model

The modules used in the proposed model are implemented through Artificial Neural Network according to its capabilities in classification and function estimation. In fact, two trained networks are consecutively put together, the first one is capable of classifying items in KPM, and the second one is capable of evaluating suppliers' performance using the output of first network along with supplier performance features.

Here it is assumed that purchasing portfolio model is not implemented in the firm yet, such that a new method is presented to map the items in the KPM. This method uses clustering analysis to detect the similar items and it organizes them as ordered clusters and locates them in the KPM quadrants. Figure 2 illustrates the KPM and four purchasing classes.

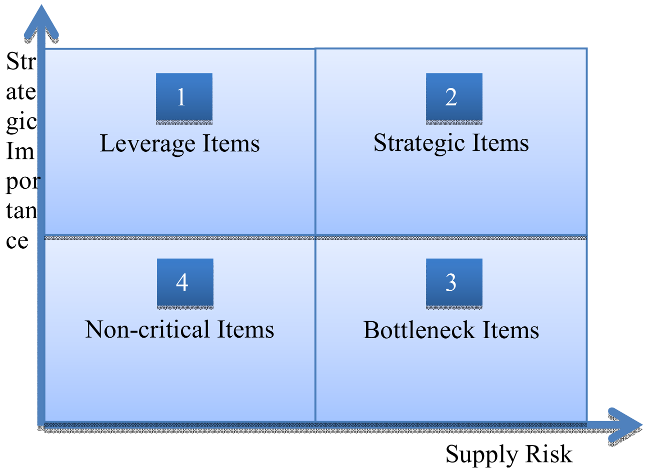

Figure 2. KPM and four purchasing classes

In order to determine the position of each item in the KPM, first the assessment criteria in each dimension of the matrix should be determined. Lee and Drake (2010) have presented a comprehensive categorization of criteria relevant to strategic importance dimension which is used here. As the manufacturing companies always compete on final products and services, the degree of the strategic importance of each purchasing item is determined by its influence on the end-product. Manufacturers use materials and components sourced from external suppliers, so their products and customer service are affected significantly by the performance of their suppliers in terms of cost, quality, time and availability (Krause and Scannell, 2002) (Lee and Drake, 2010). Thus, the Strategic Importance Score (SIS) of an item is measured using four major criteria: Cost Impact (CI), Quality Impact (QI), Delivery Impact (DI) and Service Impact (SI).

According to the difficulties of data gathering outside the organization in Small and Medium Enterprises (SME), Lee and Drake (2010) have decided to simplify the model and considered just "size of supplier" and "monopoly conditions" as the relevant criteria to supply risk dimension. Padhi, Wagner and Aggarwal (2012) have presented three major categories to address the supply risk: "market risk", "performance risk" and "complexity risk". Market risk refers to availability of the potential suppliers, monopoly conditions and entry barriers to the market, performance risk refers to supplier's quality and performance-related issues and complexity risk refers to associated problems with standardization of the product. Here, the Supply Risk Score (SRS) of an item is measured using three major criteria: Market Risk (MR), Performance Risk (PR) and Complexity Risk (CR).

The proposed method to implement the suggested model consists of three main steps illustrated in figure 3:

1. Cluster analysis to form the Kraljic Portfolio Matrix (KPM)
2. Creating the Purchasing Classification Module (PCM)
3. Creating the Performance Evaluation Module (PEM)

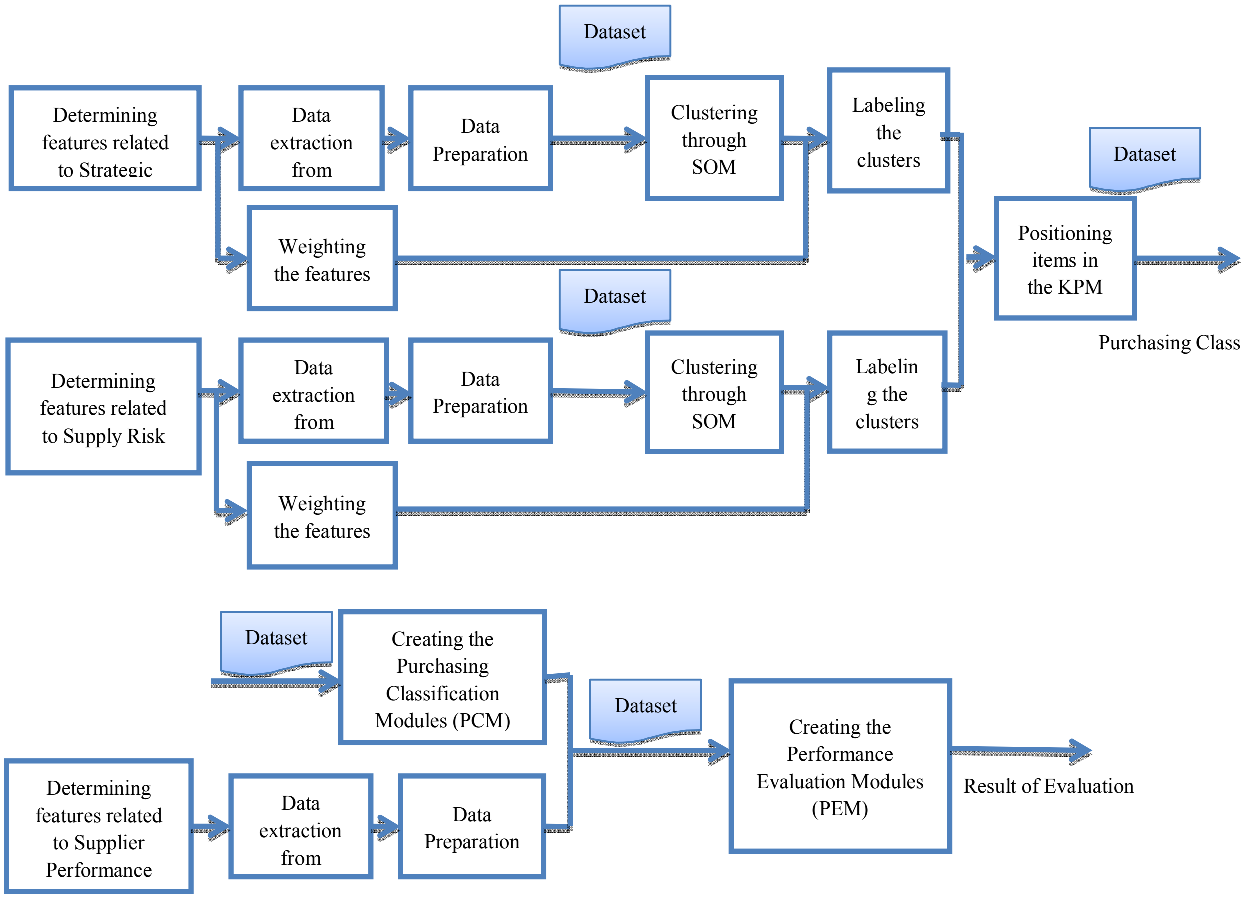

Figure 3. Proposed method to implement the model

First, the features which indicate the strategic importance should be determined. These features are divided into four categories i.e. Cost Impact (CI), Quality Impact (QI), Delivery Impact (DI) and Service Impact (SI). Then, all data related to selected features are extracted from organizational databases. At the same time, the selected features are weighted by experts that will be used for labeling the clusters. Data preparation will normalize data, and dataset_01 is obtained to perform cluster analysis. The items given in dataset_01 will be clustered using Kohonen Self-Organizing Network (KSON), and subsequently, items with similar strategic importance will be grouped in the same cluster. The number of obtained clusters depends on KSON design. For instance, a 4×4 map in the output layer of network could form at most 16 clusters. In the next step, the obtained clusters are prioritized and labeled using Strategic Importance Score (SIS) along axis Y. All items located in each cluster specify the cluster center and consequently the cluster center could be measured according to its features.

This process is once again performed on Supply Risk dimension which produces dataset_02 consisting of features related to Market Risk (MR), Performance Risk (PR) and Complexity Risk (CR). After data preparation and clustering, the obtained clusters are prioritized and labeled using Supply Risk Score (SRS) along axis X. When all items' position are determined along two dimensions, purchasing portfolio matrix will be formed and each item will be situated in one of the four classes: leverage, strategic, bottleneck and non-critical items. The border of each dimension is usually considered in the middle of each axis.

Now *dataset_03* containing all features and a specified class for each item is ready to design Purchasing Classification Module (PCM). In the next step, a classifier such as Multi-Layer Perceptron (MLP) or Radial Basis Function (RBF) is used. In classification analysis, it is recommended to design some different models and choose a model with maximum accuracy according to available data (Vercellis, 2009).

Next step consists of determining supplier performance features using organizational data bases to design supplier Performance Evaluation Module (PEM). *Dataset_04* will be formed by aggregating purchasing classes, produced by clustering analysis, and supplier performance features. It is obvious that applying multi-sourcing policy in purchasing process lets to have more than one supplier for each item and consequently leads to more records in *dataset_04* as compared to previous datasets.

Finally, as the Supplier Performance Score (SPS) is generally a non-linear function, a neural network is employed. Here, according to the capability of RBF networks in estimating non-linear functions, an RBF network is used to produce the final result.

4. Implementation and results

The proposed supplier performance evaluation model is implemented in the purchasing department of an automaker. The components of a vehicle produced in this automaker consisting 750 items are selected as a case study to form the Kraljic Portfolio Matrix (KPM) and to produce the Purchasing Classification Module (PCM). In addition, all suppliers of these items consisting 1575 records, are selected to build Performance Evaluation Module (PEM). According to multiple-sourcing policy of the company, there are usually several suppliers for each component and each supplier usually produces several components. Therefore, 750 records are considered in the first module and 1575 records are included in the second module.

Portfolio purchasing model is not yet applied in the company. Therefore, in order to create a training dataset to train the classifier module, the clustering analysis followed by positioning the purchasing items into the KPM is used. The steps of the proposed method and the obtained results are described as follows.

4.1. Creating the KPM using clustering analysis

In this paper, for the first time, clustering analysis is used to develop purchasing portfolio model. Kohonen Self-Organizing Network (KSON) is unsupervised learning ANNs applied to clustering analysis. It organizes not only the similar items in the same cluster, but also it places the similar clusters around each other. This is helpful in labeling and sorting the clusters in the desired order.

4.1.1. Data gathering for strategic importance dimension

As described, *Strategic Importance* dimension of the KPM, placed on the axis Y, is measured through four criteria: Cost Impact (CI), Quality Impact (QI), Delivery Impact (DI) and Service Impact (SI). An expert team consisting of the department managers, is gathered to explore the organizational databases and determine the features related to these criteria. Six features were selected and weighted by the expert team using AHP technique, in order to compute the *Strategic Importance Score* (SIS) for the underlying clusters. The SIS is later used in labeling the clusters and to arrange them along axis Y. Table 2 illustrates the specified features and their corresponding weights in the *Strategic Importance* dimension.

Table 2. Features and their corresponding weights in the Strategic Importance dimension

Dimension	**Strategic Importance**					
Criteria	Cost Impact (CI)		Quality Impact (QI)		Delivery Impact (DI)	Service Impact (SI)
Features	Price Share	Currency Share	Safety	Assembly Line Audit	Ordering Class	Aftermarket Grade
Weights	27.0%	31.3%	12.1%	7.9%	10.5%	11.2%

4.1.2. Creating strategic importance clusters using KSON

In order to identify different clusters in terms of *Strategic Importance*, a Kohonen network including six neurons in the input layer and a 4×4 two-dimensional maps in the output layer is designed. Figure 4a illustrates the schematic view of the designed Kohonen network and figure 4b illustrates the obtained clusters after performing KSON learning algorithm in a two-dimensional map (Karray & Silva, 2004).

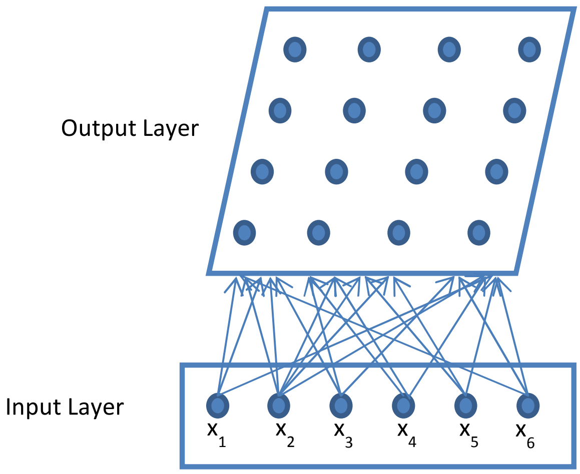

Figure 4a. Schematic view of the used KSON

Y	X: 0		X: 1		X: 2		X: 3	
3	COUNT	342			COUNT	121		
	SIS	0.0029			SIS	0.0578		
	CI	VL			CI	VL		
	QI	L			QI	L		
	DI	L			DI	M		
	SI	L			SI	L		
2					COUNT	42	COUNT	5
					SIS	0.1069	SIS	0.1648
					CI	L	CI	L
					QI	L	QI	L
					DI	H	DI	H
					SI	L	SI	M
1			COUNT	38			COUNT	18
			SIS	0.2361			SIS	0.1922
			CI	L			CI	L
			QI	M			QI	M
			DI	H			DI	H
			SI	L			SI	L
0	COUNT	73	COUNT	5	COUNT	29	COUNT	77
	SIS	0.1596	SIS	0.2760	SIS	0.3856	SIS	0.1901
	CI	L	CI	L	CI	-	CI	-
	QI	M	QI	M	QI	H	QI	M
	DI	M	DI	H	DI	H	DI	-
	SI	M	SI	M	SI	-	SI	-

VL: Very Low L: Low M: Moderate H: High VH: Very High

Figure 4b. Results of initial clustering in the Strategic Importance dimension

The output neurons compete each other to attract the items introduced to the network in the learning phase. As illustrated in the figure 4b, 10 of 16 neurons succeed to catch some items, and thus, 10 different clusters are identified. The number of items, which are attracted to each cluster, is illustrated on top of the corresponding cell in figure 4b.

The obtained 10 clusters should be arranged in Strategic Importance order and should be labeled. Thus, the SIS is computed for each cluster center. The greater the SIS, the greater the strategic importance. In addition, for each cluster, the situations of four criteria CI, QI, DI and SI are specified according to the items belonging to that cluster. For instance, all items belonging to the cluster (X=0, Y=3) demonstrate a very low Cost Impact, low Quality Impact, low Delivery Impact and low Service Impact on the end-product. The items belonging to the cluster (X=2, Y=0) demonstrate high Quality and Delivery Impact but they differ in terms of Cost and Service Impact. Therefore, clustering analysis is done again for 29 items belonging to this cluster and then 5 new clusters are appeared. Similar condition attains for the cluster (X=3, Y=0) that is divided into 6 new clusters. All obtained clusters are labeled and the neighbor clusters with few members and similar criteria are merged together. Thus, 12 clusters are obtained and sorted from C1 to C12 as illustrated in figure 5.

As can be seen, in figure 5, cluster C12 with 9 members and SIS=0.5079, has high influences on the end-product. Hence, it is the most important cluster. While cluster C1 with 342 members and SIS=0.0029, influences slightly the end-product. Hence, it is the least important cluster.

C1		C2		C3		C4		C5		C6		C7		C8		C9		C10		C11		C12	
COUNT	342	COUNT	121	COUNT	47	COUNT	37	COUNT	73	COUNT	24	COUNT	56	COUNT	13	COUNT	13	COUNT	7	COUNT	8	COUNT	9
SIS	0.0029	SIS	0.0578	SIS	0.1131	SIS	0.1309	SIS	0.1596	SIS	0.1835	SIS	0.2220	SIS	0.2654	SIS	0.3134	SIS	0.3626	SIS	0.4149	SIS	0.5079
CI	VL	CI	VL	CI	L	CI	M	CI	L	CI	M	CI	L	CI	L	CI	L	CI	M	CI	VH	CI	VH
QI	L	QI	L	QI	L	QI	M	QI	M	QI	M	QI	M	QI	M	QI	H	QI	H	QI	M	QI	H
DI	L	DI	M	DI	H	DI	M	DI	M	DI	M	DI	H	DI	H	DI	H	DI	H	DI	H	DI	H
SI	L	SI	L	SI	L	SI	L	SI	M	SI	M	SI	L	SI	M	SI	L	SI	M	SI	L	SI	H

Figure 5. Strategic Importance clusters

4.1.3. Data gathering for supply risk dimension

Supply Risk dimension of the KPM, placed on the axis X, is measured through three criteria: Market Risk (MR), Performance Risk (PR) and Complexity Risk (CR). As seen in table 3, seven features are specified and weighted to measure these criteria. Weights are applied to compute the Supply Risk Score (SRS) in order to sort the obtained clusters.

Table 3. Features and their corresponding weights in the Supply Risk dimension

Dimension	**Supply Risk**						
Criteria	Market Risk (MR)		Performance Risk (PR)		Complexity Risk (CR)		
Features	Bargaining Power	Monopoly Status	Assembly Line Stop	Assembly Line Critical	Foreign Supply	Initial Capital	Working Capital
Weights	22.2%	21.0%	21.8%	8.0%	10.4%	8.3%	8.3%

4.1.4. Creating supply risk clusters using KSON

In order to identify different clusters in terms of *Supply Risk*, a Kohonen network including seven neurons in the input layer and a 4×4 two-dimensional maps in the output layer is designed. Cluster analysis is performed to create *Supply Risk* clusters as shown in figure 6.

C1		C2		C3		C4		C5		C6		C7		C8		C9		C10		C11		C12	
COUNT	183	COUNT	247	COUNT	18	COUNT	53	COUNT	153	COUNT	20	COUNT	10	COUNT	9	COUNT	27	COUNT	11	COUNT	12	COUNT	7
SRS	0.0023	SRS	0.1058	SRS	0.1143	SRS	0.1416	SRS	0.2175	SRS	0.2335	SRS	0.3375	SRS	0.3811	SRS	0.3947	SRS	0.5106	SRS	0.5255	SRS	0.7016
MR	VL	MR	L	MR	L	MR	M	MR	M	MR	M	MR	M	MR	L	MR	H	MR	VH	MR	VH	MR	H
PR	VL	PR	VL	PR	L	PR	VL	PR	L	PR	M	PR	L	PR	H	PR	L	PR	M	PR	L	PR	H
CR	VL	CR	VL	CR	L	CR	VL	CR	L	CR	L	CR	H	CR	M	CR	L	CR	L	CR	H	CR	M

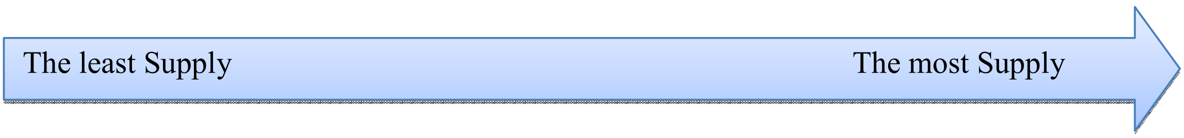

Figure 6. Supply Risk clusters

As seen in figure 6, cluster C12 with 7 members and SRS=0.5079, is the most risky cluster. While cluster C1 with 183 members and SRS=0.0023, is the least risky cluster.

4.1.5. Positioning the items in the KPM

First all items are divided into 12 Strategic Importance clusters and then all of them are divided into 12 Supply Risk clusters. Thus, a 2×2 matrix with 124 cells is produced. Each of 750 items is positioned in one of the cells. Figure 7 illustrates the produced KPM and the number of items in each cell is stated.

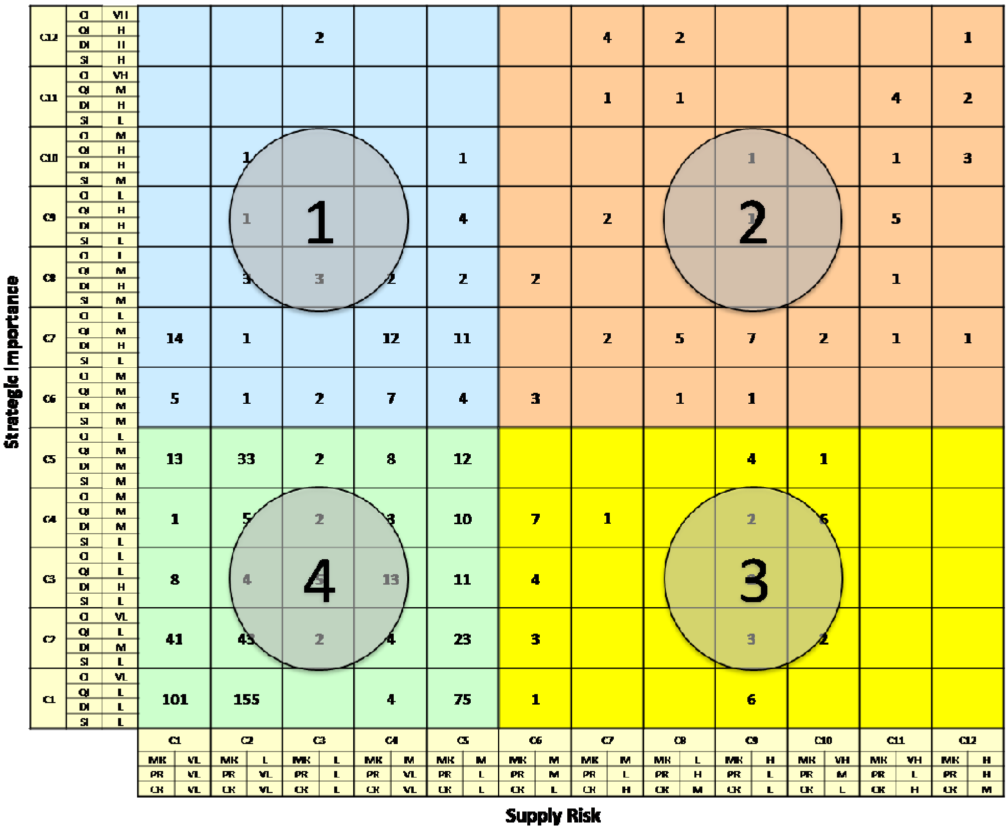

Figure 7. The KPM produced by clustering analysis

In order to determine the four purchasing classes; each dimension of the matrix is divided into two parts: low and high. The expert team are decided to fix both borders between C5 and C6 to reach a proper classification. In order to compare and verify the better situation for borders, Compactness Index is utilized as follows (Vercellis, 2009):

$$\text{Compactness Index} = \sum_{h=1}^{4} \sum_{j=1}^{n_h} \left\| \boldsymbol{x}_j - \boldsymbol{c}_h \right\|, \qquad (1)$$

where, $\boldsymbol{c}_h$ is the center of hth class and n_h is the number of items belonging to hth class. Then all 750 items are classified in 4 classes: leverage, strategic, bottleneck and non-critical.

4.2. Creating the PCM using neural networks

Creating a purchase classifier will help the purchasing department to classify other items. Required dataset for creating the Purchasing Classification Module (PCM) is prepared using the combination of two previous datasets and the results of positioning the items in the KPM. Obtained dataset_03 consists of 13 input features including 6 Strategic Importance features and 7 Supply Risk features, and also 4 outputs, the same as four existing classes. Figure 8a illustrates the schematic view of the PCM.

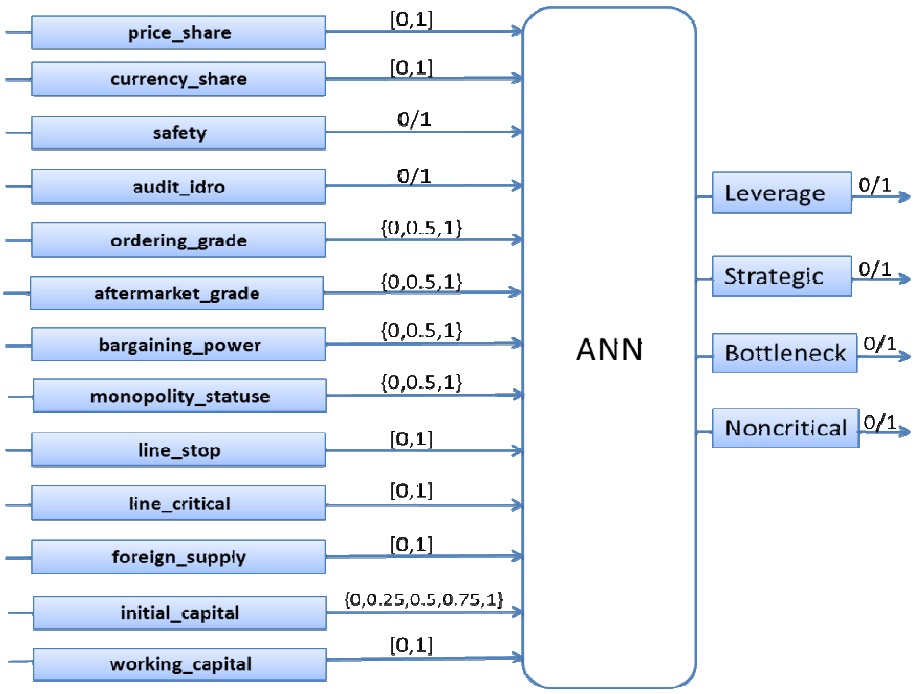

Figure 8a. Schematic view of the PCM

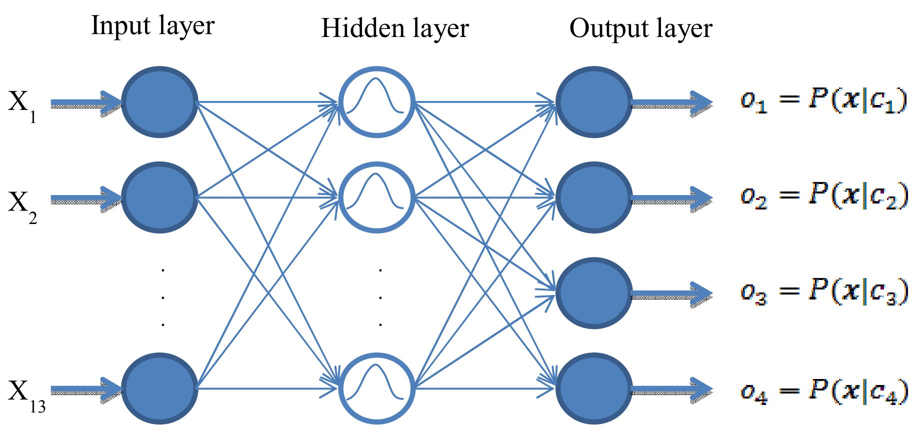

Figure 8b. Architecture of RBF network for PCM

In order to create a proper classifier, both RBF and MLP are used then according to the accuracy index, the appropriate one is selected. Both networks are designed using 13 neurons in the input layer and 4 neurons in the output layer. The suitable number of hidden neurons for both networks is determined in the validation phase using a 5-fold-cross-validation technique (Vercellis, 2009). Figure 8b illustrates the architecture of RBF network for PCM (Karray and Silva, 2004). The output class (c^*) for each input ($\boldsymbol{x}$), is determined as follows:

$$c^* = \arg\max P(\boldsymbol{x}|c_i). \tag{2}$$

For all hidden neurons, the Gaussian function with following equation is used as the activation function of neuron i.

$$g_i(\boldsymbol{x}) = \exp\left(\frac{-\|\boldsymbol{x} - \boldsymbol{v}_i\|^2}{2{\sigma_i}^2}\right), \tag{3}$$

where, σ_i is the width of ith hidden neuron that is determined in the validation phase according to the accuracy index as given by:

$$\text{accuracy} = 1 - \frac{1}{n}\sum_{i=1}^{n} L(\mathrm{y_i}, f(\boldsymbol{x}_i)), \tag{4}$$

where, y_i is the target class for ith instance in the validation dataset, $\boldsymbol{x}_i$ is the input vector, $f(\boldsymbol{x}_i)$ is the output of the network for that instance and n is the number of instances in the validation dataset. $L(y_i, f(\boldsymbol{x}_i))$ is the Loss function which is defined as following:

$$L(\mathrm{y_i}, f(\boldsymbol{x}_i)) = \begin{cases} 0, & if \quad y_i = f(\boldsymbol{x}_i) \\ 1, & if \quad y_i \neq f(\boldsymbol{x}_i). \end{cases} \tag{5}$$

After examining different amounts of width for the activation function, and also the different numbers of the hidden neurons and training the network, an RBF network is obtained with 50 hidden neurons and Gaussian activation functions with σ=0.8. The obtained classifier is examined using the test dataset and it could classify the test instances with 95% accuracy. Figures 9a and 9b illustrate the results.

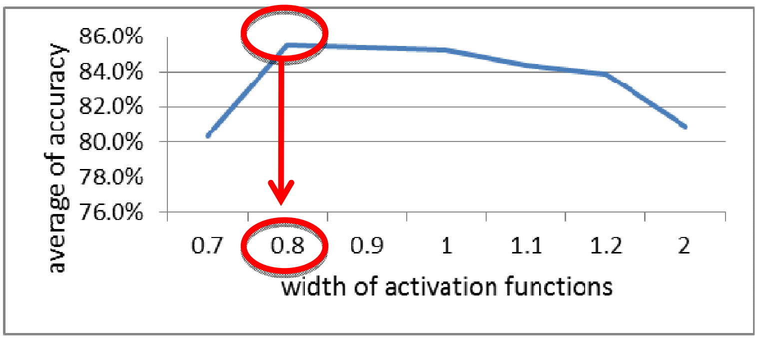

Figure 9a. The best amount for activation function width

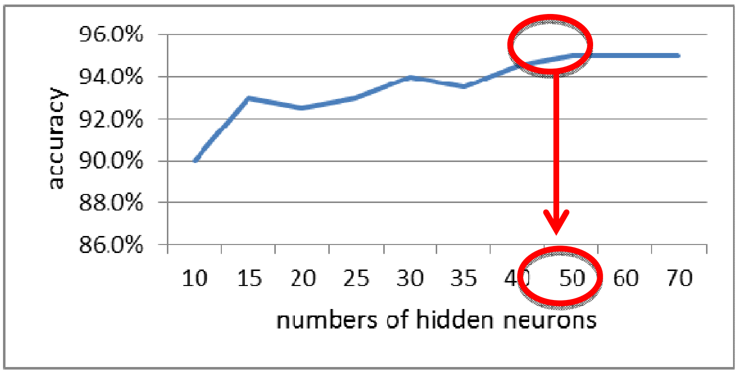

Figure 9b. The best number of hidden neurons

Once again an MLP network is designed using available datasets. This time, a network including 13 neurons in the input layer, 8 neurons in the hidden layer and 4 neurons in the output layer is designed as the best MLP network for the available data. The obtained classifier is evaluated using the test dataset and it could classify the test instances with 87.5% accuracy. Hence, the most accurate RBF network is selected as the most proper PCM for available data.

4.3. Creating the PEM using neural networks

Researchers who applied ANN to develop the supplier performance evaluation model usually used MLP network to classify suppliers into different performance classes (Ha and Krishnan, 2008) (Temur, Özdemir and Kaya, 2009) (Aksoy and Öztürk, 2011). Here, instead of classifying suppliers into different performance classes, a neural network is designed to evaluate the supplier performance with a continuous score to promote the evaluation precision. Continuous performance scoring could be useful to monitor the supplier improvement during the cooperation period. Therefore, Supplier Performance Score (SPS) is considered as a function of evaluation criteria and an RBF network is used to create Performance Evaluation Module (PEM). Purchasing class which is the output of PCM is also considered as an input variable to the PEM in order to evaluate each supplier according to the corresponding purchasing class.

Table 4. Supplier Performance Features

Performance Criteria	**Performance features**
Quality	Supplier Quality Grade, Supplier Quality Assurance (SQA) Documentation, Quality Auditing Result, Defect Parts Per Million (PPM)
Price	Competitive Price
Delivery	Order Fulfillment, On-time Delivery, Extra Delivery in Critical Situations

Selecting appropriate measuring criteria to evaluate supplier performance depends on the organization purchasing procedure and is done by the expert team. Here, supplier performance factors in three groups: Quality Performance, Price Performance and Delivery Performance including 8 different features as illustrated in table 4 are considered as the PEM inputs and then available data for these features are drawn out from the organizational databases.

A computer-aided supplier performance system is already applied to the studied department which monthly evaluates all suppliers. Thus, the last result of the supplier performance system is drawn out from the organizational databases and the obtained data is considered as the target output to create the PEM. Figure 10a illustrates all input and output variables used to construct the PEM.

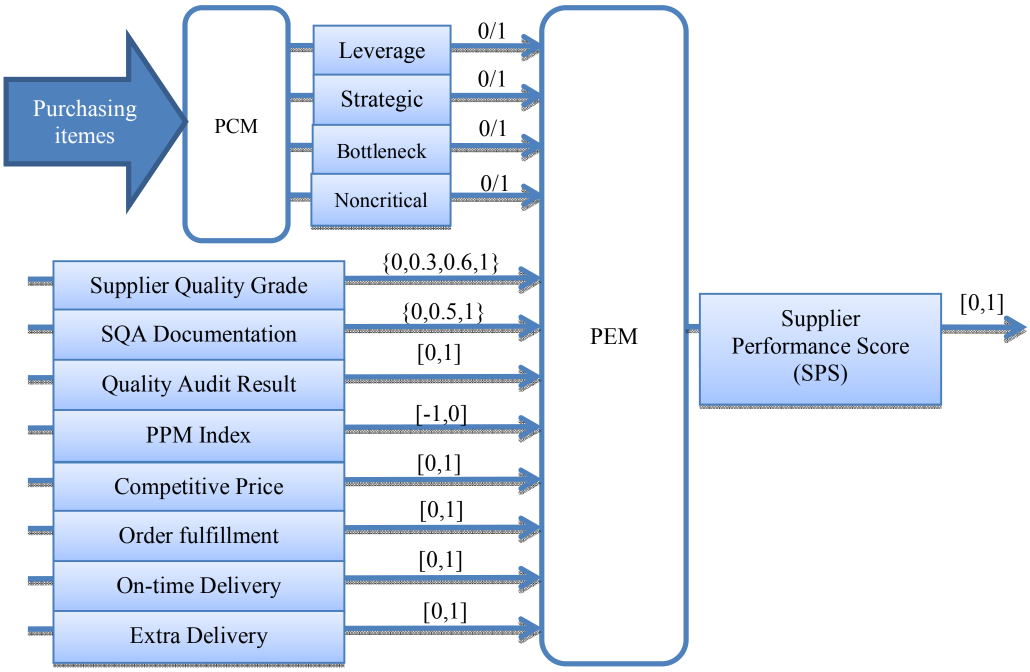

Figure 10a. Input and output variables used to construct the PEM

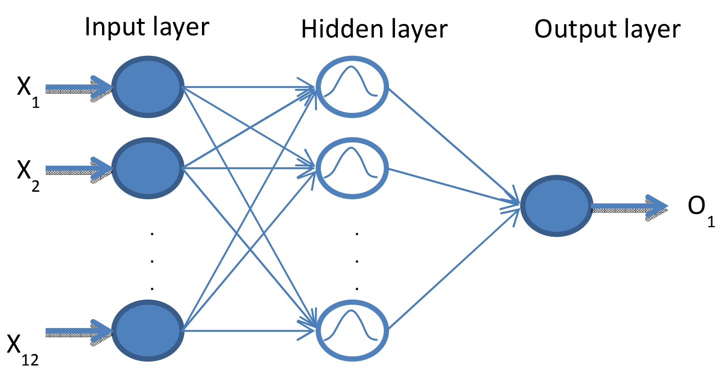

Figure 10b. Architecture of RBF network for PEM

In order to design the PEM, *dataset_04* is prepared using the combination of 8 performance features and 4 purchasing classes as the input variables and also the Supplier Performance Score (SPS) as the only output variable. Hence, an RBF network including 12 neurons in the input layer and one neuron in the output layer is considered to implement the PEM. Figure 10b illustrates the architecture of RBF network for PEM.

Using 5-fold cross validation technique, the RBF network with different amounts of the width and also different number of hidden neurons is trained and each time, accuracy of the network is computed. Here, Mean Squared Error (MSE) is used to compare the networks' accuracy and the RBF network with minimum MSE is selected.

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}\left(\mathrm{y_i} - f(\boldsymbol{x}_i)\right)^2 \tag{6}$$

Figures 11a and 11b illustrate different amounts of width and also different numbers of hidden neurons examined to achieve the best design for the RBF network. As a result, an RBF network with 50 hidden neurons and σ=2.3 is selected as the best solution. As result, trained network is tested using the test dataset and it is validated regarding to its capability to estimate the SPS with maximum 0.2% error.

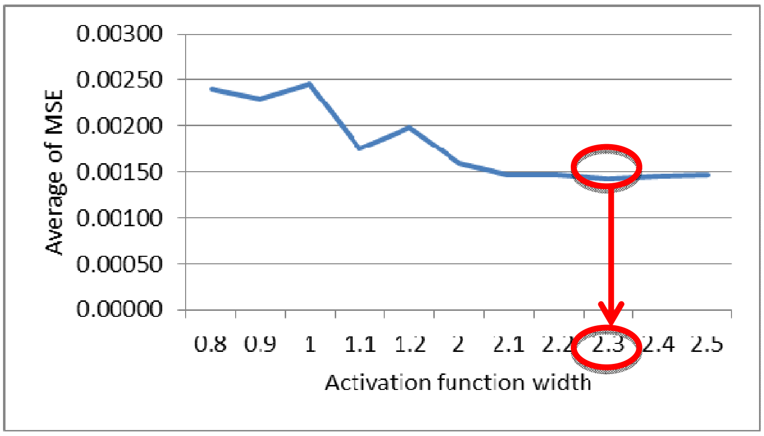

Figure 11a. The best amount for the width radial function

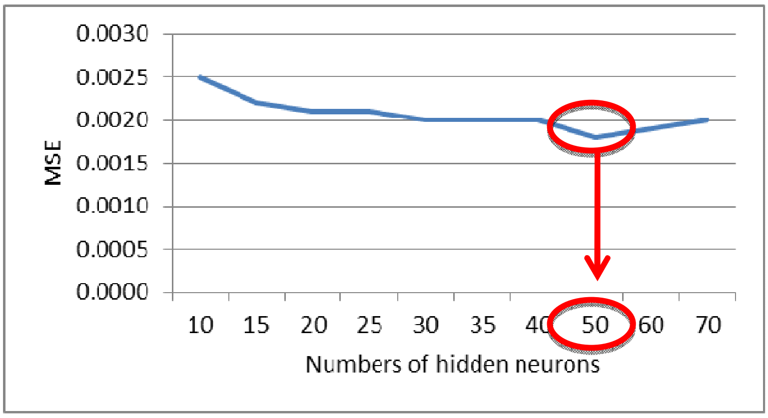

Figure 11b. The best number of hidden neurons

5. Conclusion

In this paper a new method is presented to develop the purchasing portfolio model using the available data in the organizational information system by cluster analysis. Using the produced data in clustering step and purchasing items features, a classifier Neural Network is developed to categorize new purchasing items in the KPM. In addition, a Neural Network is developed to assess supplier performance score using purchasing classes and supplier performance features. These specifications turn the proposed model a suitable and applicable model to strategic purchasing management.

Since the supplier performance evaluation is periodically done e.g. three month periods, in future, a supplier performance forecasting model could be developed using time series and capabilities of ANN in creating forecasting models. Meanwhile according to the utilization of KSON technique for cluster analysis here, other clustering methods could be used to improve the results.

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