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Comparative Data MiningTechniques for Clustering items in a Multi-Layer and Multi-Product Supply Chain

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This paper concerns with clustering elements in a multi-layer and multi-product supply chain aiming purification of interactions using data mining. The goal is to improve the performance of the supply chain and preventing the bottlenecks. Thus, data mining techniques are applied for clustering elements configure the proposed supply chain using operational specifications related to each layer of the supply chain. Here, we propose a multi-clustering system to cluster the elements of a supply network based on the similarity in information flow.We apply data mining techniques as decision aid in our supply chain.

Keywords: Multi-Layer; Multi-Product; Supply Chain; Clustering Techniques

INTRODUCTION

The current business environment is becoming increasingly complex, uncertain, unpredictable, and as a result, more and more competitive. As competition and complexity have increased, flexibility-based supply chain management (SCM) has emerged as an increasingly important issue for companies. The challenge of flexibility in SCM is to identify and implement strategies which minimize cost while maximizing flexibility in an increasingly competitive and complex market (Browne et al., 1997; Wadhwa and Saxena, 2005). Flexibility stands out as the most discussed and applied domain in manufacturing and supply chains (SCs) (Browne et al., 1995; Chan et al., 2006; Stecke and Solberg, 1981). Sushil (2000) while deliberating upon the concept of systematic flexibility has essentially stressed the multiplicity of connotations of flexibility in response to diversity of situations. Wadhwa and Rao (2000) defined flexibility as the ability to deal with change by judiciously providing and exploiting controllable options dynamically. The potential of certain types of flexibility to enhance the overall performance of manufacturing and supply chain system has attracted the attention of many researchers (for example, (Wadhwa et al., 2005; Browne et al., 1984; Chan et al., 2004)). Flexibility implications on the SCs performance need to be more closely understood as most researcher shave interpreted it differently. Enhanced competitiveness requires that companies ceaselessly integrate within a network of organizations. Firms ignoring this challenge are destined to fall behind their rivals. This integration of companies within a network has led to put more emphasis on supply chain management (SCM). “SCM is the management of upstream and downstream relationships in order to deliver superior customer value at less cost to the supply chain as a whole” (Christopher, 1998). The integral value of the SCM philosophy is that “total performance of the entire supply chain is enhanced when we simultaneously optimize all the links in the chain as compared to the resulting total performance when each individual link is separately optimized (Burke and Vakkaria, 2002).

Recent technological developments in information systems and information technologies have the potential to facilitate this coordination, and this, in turn, allows the virtual integration of the entire supply chain. The focus of this integration in the context of internet-enabled activities is generally referred to as e-SCM. Merging these two fields (SCM and the internet) is a key area of concern for contemporary managers and researchers. Managers have realized that the internet can enhance SCM decision making by providing real-time information and enabling collaboration between trading partners. Many companies have implemented point-of-sales scanners, which read, on real time, what is being sold. These companies do not only collect information on real-time to make decisions about what to order or how to replenish the stores; they also send this information, through the internet, to their suppliers in order to make them able to synchronize their production to actual sales.

Following the definition of SCM of Cooper et al. (1997), we define e-SCM as the impact that the internet has on the integration of key business processes from end-user through original suppliers that provides products, services and information that add value for customers and other stakeholders. The main objective of this paper is to identify the major issues surrounding the impact of the internet on SCM, focusing on supply chain processes. The internet can have three main impacts on the supply chain. One of the most covered topics in the literature is the impact of e-commerce, which refers mainly to how companies can respond to the challenges posed by the internet on the fulfillment of goods sold through the net. Another impact refers to information sharing, how the internet can be used as a medium to access and transmit information among supply chain partners. However, the internet not only enables supply chain partners to access and share information, but also to access data analysis and modeling to jointly make a better planning and decision making. This jointly planning and decision making is the third type of impact of the internet on SCM and we refer to it as knowledge sharing.

As Croom (2005) pointed out very recently, there is some debate about the scope of SCM. For example, Oliver and Webber (1992) and Houlihan (1984) used the term SCM for the internal supply chain that integrates business functions involved in the flow of materials and information from inbound to outbound ends of the business. Ellram (1991) viewed SCM as an alternative to vertical integration. Cooper et al. (1997) defined SCM as “the integration of key business processes from end-user through original suppliers that provides products, services, and information that add value for customers and other stakeholders”. And, Christopher (1998) defined SCM as the management of upstream and downstream relationships. Croom (2005) suggested that one way of dealing with the diversity of SCM definitions is to concentrate on the core processes and functions relating to the management of supply chains (for example, fulfillment, operations planning and procurement).

In the literature there is a diversity of models suggesting the main supply chain processes. For example, the Supply Chain Operations Reference (SCOR) model developed in 1996 focuses on five key processes: plan, source, make, deliver and return. Cooper et al. (1997) defined SCM taking into account the eight supply chain processes identified by the International Centre for Competitive Excellence (now named Global Supply Chain Forum): customer relationship management (CRM), customer service management, demand management, fulfillment, procurement, manufacturing flow management, product development and commercialization and reverse logistics. Hewitt (1994) found that executives identify up to 14 business processes. As a result, a definition comprising a number of processes closer to 14 might provide more detailed information for practitioners and researchers. Accordingly, from the two previous models we decided to adopt the definition of SCM provided by Cooper et al. (1997). This definition has been widely referred to (Romano and Vinelli, 2001; Cagliano et al., 2003; Mills et al., 2004; Cousins, 2005; Danese et al., 2006).

Given the rate of growth of the Web, proliferation of e-commerce, Web services, and Web-based information systems, the volumes of clickstream and user data collected by Web-based organizations in their daily operations has reached huge proportions. Meanwhile, the substantial increase in the number of websites presents a challenging task for webmasters to organize the contents of the websites to cater to the needs of users (Cooley et al., 1997). Modeling and analyzing web navigation behavior is helpful in understanding what information of online users demand. Following that, the analyzed results can be seen as knowledge to be used in intelligent online applications, refining web site maps, web based personalization system and improving searching accuracy when seeking information. Nevertheless, an online navigation behavior grows each passing day, and thus extracting information intelligently from it is a difficult issue (Wang and NetLibrary, 2000). Web usage mining refers to the automatic discovery and analysis of patterns in clickstream and associated data collected or generated as a result of user interactions with Web resources on one or more Web sites (Srivastava et al., 2000).

In this research, supply network elements in a multilayer structure are considered to have online interactions. Since many elements in various layer may have common interests up to a point during their online interactions, information flow patterns should capture the overlapping interests or the information needs of these elements. In this study we advance a model for clustering the supply network elements.

PROBLEM DESCRIPTION

To maintain competitiveness, manufacturers are seeking to deliver high-quality products at affordable prices to customers.In order to improve the performance in multi-layer and multi-product supply chain, we consider a five layer supply chain as shown in Fig.1 where manufacturers produce different products.The problem of supply chain performance can be shown as follows:

The counters for different elements of the model are given below.

Suppliers Layer={s1,s2,s3,…,si}
Manufacturers Layer={m1,m2,m3,…,mj}
Distributers Layer={d1,d2,d3,…,dk}
Retailers Layer={r1,r2, r3,…,rl}
Customers Layer={c1,c2,c3,…cm}

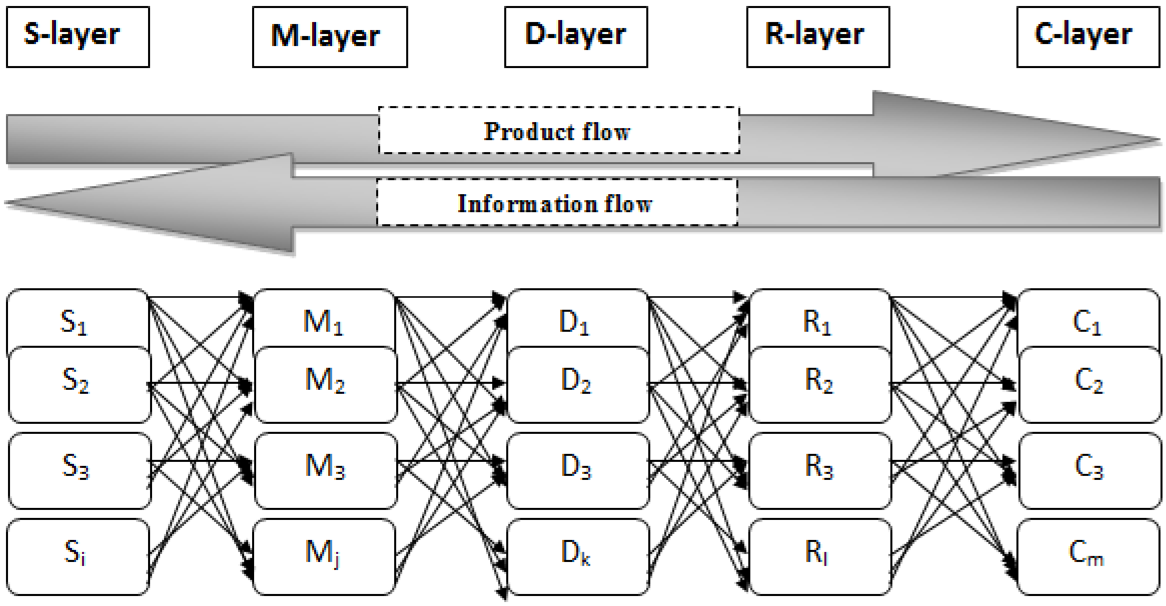

Figure 1.Forward and Backward flow in multi-layer supply chain

Each of these layers makes decisions based on the information they have about the prior and next layers. It can be shown that these series of decisions do indeed lead to the best overall performance from start to finish. This is achieved by selecting the best available option at each stage.

To clarify, let us consider a manufacturer that should select an appropriate supplier through suppliers' layer in multi-layer supply chain as shown in Fig. 1.It is vital for both operational and informational performance of supply chains.We will use Data mining techniques in order to improve supply chain performance.Indeed we apply clustering in each layer separately and it will lead to better decision making for each layer and finally improvement in the whole supply chain. The clustering is based on some operational specifications.

With regard to the use of data mining in recent years in various industries, considering production is on the rise alsoall the platforms for data mining, including high-speed data processing, data warehousing, data analysis and data mining software are available.So,data mining can be used to improve the performance of supply chain in manufacturing.

The purpose of our study is providing a framework to improving performance of multi-product multi-layer supply chain using data mining techniques and knowledge discovery. Through this framework,we can improve supply chain performance and meet customer needs.Also, using this knowledge in supply chain management provide customers' consent.

DATA MINING

Data mining processes can be divided to six sequential, iterative steps:

1. Problem definition
2. Data acquisition
3. Data preprocessing and survey
4. Data modeling
5. Evaluation
6. Knowledge deployment

Each step is essential: The problem defines what data are used and what is a good solution. Modeling makes it possible to apply the results to new data. On the other hand, data modeling without good understanding and careful preparation of the data leads to problems. Finally, the whole mining process is meaningless if the new knowledge will not be used (Pyle, 1999).

CLUSTERING ALGORITHMS

Clustering algorithms may be classified as listed below:

1. Exclusive Clustering

2. Overlapping Clustering
3. Hierarchical Clustering
4. Probabilistic Clustering

In the first case data are grouped in an exclusive way, so that if a certain datum belongs to a definite cluster then it could not be included in another cluster.
On the contrary the second type, the overlapping clustering, uses fuzzy sets to cluster data, so that each point may belong to two or more clusters with different degrees of membership. In this case, data will be associated to an appropriate membership value.
Instead, a hierarchical clustering algorithm is based on the union between the two nearest clusters. The beginning condition is realized by setting every datum as a cluster. After a few iterations it reaches the final clusters wanted.
Finally, the last kind of clustering uses a completely probabilistic approach.
Here, four of the most used clustering algorithms are considered as follows:

1. K-means
2. Fuzzy C-means
3. Hierarchical clustering
4. Mixture of Gaussians

Each of these algorithms belongs to one of the clustering types listed above. So that, K-means is an exclusive clustering algorithm, Fuzzy C-means is an overlapping clustering algorithm, Hierarchical clustering is obvious and lastly Mixture of Gaussian is a probabilistic clustering algorithm.

DISTANCE MEASURE

An important component of a clustering algorithm is the distance measure between data points. If the components of the data instance vectors are all in the same physical units then it is possible that the simple Euclidean distance metric is sufficient to successfully group similar data instances. However, even in this case the Euclidean distance can sometimes be misleading. Despite both measurements being taken in the same physical units, an informed decision has to be made as to the relative scaling. Notice however that this is not only a graphic issue: the problem arises from the mathematical formula used to combine the distances between the single components of the data feature vectors into a unique distance measure that can be used for clustering purposes: different formulas leads to different clustering.
Again, domain knowledge must be used to guide the formulation of a suitable distance measure for each particular application. For higher dimensional data, a popular measure is the Minkowski metric,

$$d_p(x_i, x_j) = \left(\sum_{k=1}^{d} \left|x_{i,k} - x_{j,k}\right|^p\right)^{\frac{1}{p}},$$

where d is the dimension of the data. The Euclidean distance is a special case, where p=2, while Manhattan metric has p=1. However, there are no general theoretical guidelines for selecting a measure in any given application. A clustering Q means partitioning a data set into a set of clusters Qi, i=1,…,C. In crisp clustering, each data sample belongs to exactly one cluster (Bezdek and Pal, 1992). Fuzzy clustering is a generalization of crisp clustering where each sample has a varying degree of membership in all clusters. Clustering can also be based on mixture models (McLahlan and Basford, 1987). In this approach, the data are assumed to be generated by several parameterized distributions (typically Gaussians). Distribution parameters are estimated using, for example, the expectation-maximization algorithm. A widely adopted definition of optimal clustering is a partitioning that minimizes distances within and maximizes distances among clusters. However, this leaves much room for variation: within- and between-cluster distances can be defined in several ways; see Table I. The selection of the distance criterion depends on the application. The distance norm $\|.\|$ is yet another parameter to consider. Here, we use the Euclidean norm. We utilize local criteria in clustering data. Thus, S_{nn} and ds in Table 1 are based on distance to nearest neighbor. In Table 3, $x_i, x_{i'} \in Q_k$, for $i \neq i'$, $x_j \in Q_l$, $k \neq l$, N_k is the number of samples in cluster Q_k, and $c_k = \frac{1}{N_k}\sum_{x_i \in Q_k} x_i$. However, the problem is that they are sensitive to noise and outliers. Addition of a single sample to a cluster can radically change the distances (Bezdek, 1998). To be more robust, the local criterion should depend on collective features of a local data set (Blatt et al., 1996). Solutions include using more than one neighbour (Karypis et al., 1999) or a weighted sum of all distances.

Table 1. Within-cluster and between-clusters distances

Within-cluster distance	**S(Qk)**
Average distance	$S_a = \frac{\sum_{i,i'} \lVert x_i - x_{i'} \rVert}{N_k(N_k - 1)}$
Nearest neighbor distance	$S_{nn} = \frac{\sum_i \min_{i'} \{\lVert x_i - x_{i'} \rVert\}}{N_k}$
Centroid distance	$S_c = \frac{\sum_i \lVert x_i - c_k \rVert}{N_k}$
Between-clusters distance	D(Qk,Ql)
Single linkage	$d_s = \min_{i,j} \{\lVert x_i - x_j \rVert\}$
Complete linkage	$d_{co} = \max_{i,j} \{\lVert x_i - x_j \rVert\}$
Average linkage	$d_a = \frac{\sum_{i,j} \lVert x_i - x_j \rVert}{N_k . N_l}$
Centroid linkage	$d_{ce} = \lVert c_k - c_l \rVert$

CLUSTERING TECHNIQUES

Complete-linkage clusteringfurthest neighbor is one of several methods of agglomerative hierarchical clustering. In the beginning of the process, each element is in a cluster of its own. The clusters are then sequentially combined into larger clusters, until all elements end up being in the same cluster. At each step, the two clusters separated by the shortest distance are combined. The definition of 'shortest distance' is what differentiates between the different agglomerative clustering methods. In complete-linkage clustering, the link between two clusters contains all element pairs, and the distance between clusters equals the distance between those two elements (one in each cluster) that are farthest away from each other. The shortest of these links that remains at any step causes the fusion of the two clusters whose elements are involved. The method is also known as farthest neighbor clustering. The result of the clustering can be visualized as a dendrogram, which shows the sequence of cluster fusion and the distance at which each fusion took place.

Nearest neighbor Single-Link is one of several methods of agglomerative hierarchical clustering. In the beginning of the process, each element is in a cluster of its own. The clusters are then sequentially combined into larger clusters, until all elements end up being in the same cluster. At each step, the two clusters separated by the shortest distance are combined. The definition of 'shortest distance' is what differentiates between the different agglomerative clustering methods. In single-linkage clustering, the link between two clusters is made by a single element pair, namely those two elements (one in each cluster) that are closest to each other. The shortest of these links that remains at any step causes the fusion of the two clusters whose elements are involved. The method is also known asnearest neighbor clustering. The result of the clustering can be visualized as a dendrogram, which shows the sequence of cluster fusion and the distance at which each fusion took place.

Average linkage within groups is a method of calculating distance between clusters in hierarchical cluster analysis. The linkage function specifying the distance between two clusters is computed as the distance between the average values (the mean vectors or centroids) of the two clusters.

A FRAMEWORK

In this section, we explain our proposed framework and provide an algorithm for application purpose. The proposed framework is given in Figure 2. Firstly, for clustering each layer, we need someperformance indicators. So,by reviewingthe literature in performance indicators field for supply chain, we select some of important indicators in each layer and start clustering by the proposed developed K-means algorithm.Finally, we use a Questionnaire to collect the feedback of customer knowledge about products and services in order to transfer their knowledge to the related layer in supply chain to apply those for performance improvement.

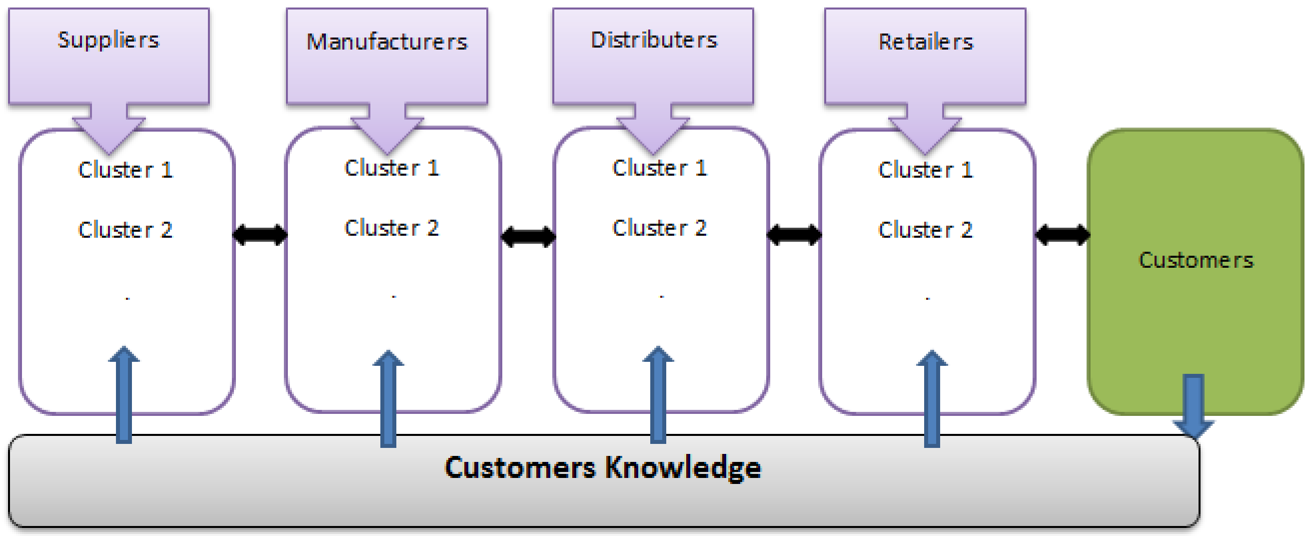

Figure 2. Proposed Framework

The common k-means clustering algorithm is given below:

1: Select K points as the initial centroids.
2: **repeat**
3: Form K clusters by assigning all points to the closest centroid.
4: Recompute the centroid of each cluster.
5: **until** The centroids don't change

But, due to drawbacks of the algorithm for our problem, a developed version of k-means algorithm is provided by adding some steps as follows:

SOLUTIONS TO INITIAL CENTROIDS PROBLEM:

- Multiple runs helps, but probability is not on your side
- Sample and use hierarchical clustering to determine initial centroids
- Select more than k initial centroids and then select among these initial centroids
  Select most widely separated
- Post processing
- Bisecting K-means

Not as susceptible to initialization issues

In order to select appropriate initial centroids (K), we use hierarchical clustering to determine initial centroids for Step1 in k-means algorithm. In Backward flow in order to extract customer knowledge, we use a Questionnaire and analyze thefilled questionnaires by Excel package then results are shown by pie charts.

Here, we describe our multilayer agent based electronic supply network. As stated before, our proposed network consists of five layers. Suppliers should provide raw materials for factories to make a product and present at the markets. In our proposed model, all suppliers present their goods in their web sites and any manufacturer visit the web sites and collect the information about the suppliers. Then, using the proposed intelligent agent the ranking of suppliers, data analysis and data saving is performed.

The next layer is for manufacturers. Manufacturers exchange their manufacturing data with each other through World Wide Web. These data are collected and analyzed via an intelligent agent. The intelligent agent work out as a decision aid and provide the information such as machine information, production processes, depot analysis and optimization, and manufacturing optimizations. The results are saved in the corresponding data base and viewed for public visit in an internet web site. The third and fourth layers are distributors and retailers. Here, an interaction between distributor and retailer is considered. Distributors conduct their depot information, due dates, order list and etc., to the internet using an information sharing mechanism. The vehicles of distributors are connected to a server and report real time information about the delivery of products to retailers. Retailers' interests, need and orders are given in their corresponding web sites and deposited in a data base.

Here, the intelligent system collect the information from different servers, analyze them and provide a report containing orders in transit, orders delivered, orders sent and distributor depot inventory control. The last layer of our proposed multilayer e-SCM contains an interaction between retailer and customer. Customers present their interest and needs in a local server. The data are saved in the market data bases and transferred to the World Wide Web. At the same time, retailers show their products and their specifications in another local server, and therefore transfer them to retailer data base. The intelligent agent collects the information from both sides and help retailers in decision making about the customer relationship management through web, electronic quality function deployment. For customers the decisions may be about modifying the interests due to product specifications, and procurement through web.

Considering the interactions amongst elements of our proposed multilayer e-SCM, an information flow exists which implies the information and data exchanges between any two layer via intelligent agents. We want to develop a new clustering methodology to segment the elements in different layers. This method is based on the information flow between any two elements in virtual environment. The aim of this segmentation is to improve the serviceability of the network and to increase the flexibility of the network for presenting multi commodity markets. The intelligent agents record and trace the data transfer and exchange between and within the layers. All the information are transferred and saved in a main data base. The clustering is performed based on the data of the main database.

We introduce selected performance indicators for each layer as follows:

Supplier layer:

- Warehousing cost
- Inventory cost
- Total logistic cost
- Rejection percent
- On time Delivery percent
- Delivery lead time

Manufacturer layer:

- Delivery lead time
- On time Delivery percent
- Rejection percent
- Total logistic cost
- Inventory cost
- Warehousing cost
- Failure rate
- Production cost
- Delivery time

Distributer layer:

- Warehousing cost
- Inventory cost
- Total logistic cost
- Rejection percent
- On time Delivery percent
- Delivery lead time
- Distribution cost

Retailer layer:

- On time Delivery percent
- Delivery lead time
- Warehousing cost
- Inventory cost
- Rejection percent

CASE STUDY

To show applicability of the proposed clustering model a numerical example is developed. Consider the supplier and manufacturer layers each having several items (11 suppliers;26 manufacturers, 7 distributors, 34 retailers). The aim is to cluster suppliers and manufactures and allocate the suitable suppliers to manufactures based on the similarity index extracted from the performance criteria listed below:

Supplier layer:

- Warehousing cost
- Inventory cost
- Total logistic cost
- Rejection percent
- On time Delivery percent
- Delivery lead time

Manufacturer layer:

- Delivery lead time
- On time Delivery percent
- Rejection percent
- Total logistic cost
- Inventory cost
- Warehousing cost
- Failure rate
- Production cost
- Delivery time

Distributer layer:

- Warehousing cost
- Inventory cost
- Total logistic cost
- Rejection percent
- On time Delivery percent
- Delivery lead time
- Distribution cost

Retailer layer:

- On time Delivery percent
- Delivery lead time
- Warehousing cost
- Inventory cost
- Rejection percent

The related data for 100 periods were collected and employed for clustering purpose. The data are inserted in a pseudo code developed in SPSS software and the clustering using distance measure in an expanded k-mean algorithm provides results. The clustering result based on the developed k-mean technique is given in Table 2. Also, the process of clustering is shown in Figure 3.

Table 1. Clustering results

	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
Suppliers	5,6,9,11	1,3,7	2,4,8	10	-
Manufactures	4,7,10,14,19,23	5,6,17,22,25	1,8,11,13,16,20	3,9,12,15,18	2, 21,24,26
Distributor	3,4,6	1,5	2,7	-	-
Retailer	1,7,11,14,17,22,23,24,27	5,12,19,29,31,35	2,8,13,18,25,30,34	3,4,9,15,20,26,32,36	6,10,16,21,28,33

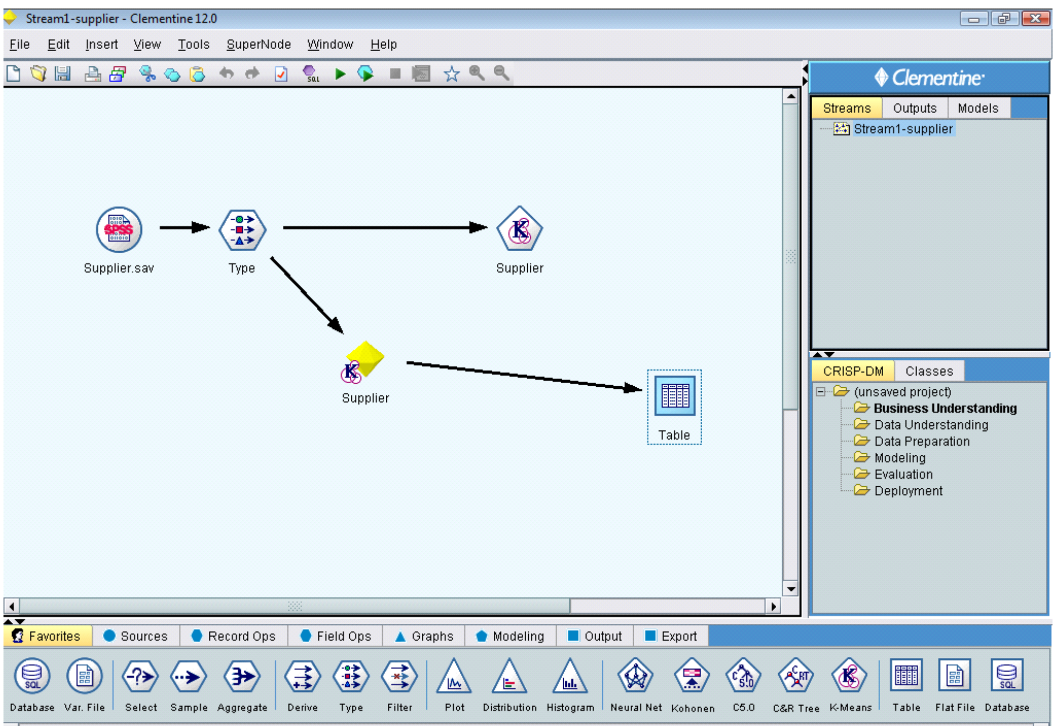

Figure 3.Supplier layer clustering model

The results show that items having similar performance criteria based on distance measure are in a same cluster. Thus, items in different layers are in homogenous clusters to better determination of multiple supplier selection. This decision is a strategic one in the supply chain literature.

In the next stage the allocation of suppliers to manufacturers is aimed. This allocation helps the management to periodic decision making based on the performance criteria in various circumstances. The allocation results are given in Tables3-5.

Table 3. Allocation results in the first layer (supplier-manufacturer)

Suppliers Manufactures	**Cluster 1**	**Cluster 2**	**Cluster 3**	**Cluster 4**
Cluster 1		*		
Cluster 2			*	
Cluster 3		*		
Cluster 4				*
Cluster 5	*			

Table 4. Allocation results in the second layer (manufacturer-distributor)

Manufactures Distributor	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
Cluster 1	*				*
Cluster 2		*	*		
Cluster 3			*		*

Table 5. Allocation results in the first layer (distributor -retailer)

Distributor Retailer	Cluster 1	Cluster 2	Cluster 3
Cluster 1	*		
Cluster 2			*
Cluster 3	*		
Cluster 4		*	
Cluster 5			*

For comparison purpose the introduced clustering techniques are modeled to be compared with the results obtained by the adapted k-means algorithm. Therefore, we run the data by the Complete-linkage clusteringfurthest neighbor, Nearest neighbor Single-Link and Average linkage within groups. A criterion for comparison is the mean distance deviation from the centroid. The computations were shown in Table 6. The values show the mean distance deviation for all entries from different techniques in each layer.

Table 6. Clustering techniques clustering

Techniques Mean distance deviation from centroid	Complete-linkage furthest neighbor	Nearest neighbor Single-Link	Average linkage within groups	The adapted k-means
Supplier	125.7	142.3	135.5	119.8
Manufacturer	112.6	116.9	113.8	107.4
Distributor	97.4	92.1	95.5	88.1
Retailer	101.1	90.9	98.2	85.4

The results show that the adapted k-means algorithm employed in this research has lower deviation values in all layers and for all clusters. Thus, the method is efficient in comparison with the given clustering techniques.

CONCLUSIONS

In this paper a new clustering technique based on k-mean algorithm was developed. The basis of the algorithm was based on distance measure. A multi-layer multi-item supply chain was proposed and modeled. A strategic decision making in supply chain was to cluster the items in each layer and then allocate the similar clusters to each other regarding the performance criteria. Also, to test the efficiency of the adapted method comparisons were done with Complete-linkage clusteringfurthest neighbor, Nearest neighbor Single-Link and Average linkage within groups. The numerical results show the applicability of the proposed methodology.

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