Data mining Aided Proficient Approach for Optimal Inventory Control in Supply Chain Management

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Abstract- Optimal inventory control is one of the significant tasks in supply chain management. The optimal inventory control methodologies intend to reduce the supply chain (SC) cost by controlling the inventory in an effective manner, such that, the SC members will not be affected by surplus as well as shortage of inventory. In this paper, we propose an efficient approach that effectively utilizes the Data Mining (DM) concepts as well as Genetic Algorithm (GA) for optimal inventory control. The proposed approach consists of two major functions, mining association rules for inventory and selecting SC cost-impact rules. Initially, the association rules are mined from EMA-based inventory data, which is determined from the original historical data. Apriori, a classic data mining algorithm is utilized for mining association rules from EMA-based inventory data. Later, with the aid of genetic algorithm, SC cost-impact rules are selected for every SC member. The obtained SC cost-impact rules will possibly signify the future state of inventory in any SC member. Moreover, the level of holding or reducing the inventory can be determined from the SC cost-impact rules. Thus, the SC cost-impact rules that are derived using the proposed approach greatly facilitate optimal inventory control and hence make the supply chain management more effective.

Index Terms - Data mining, Genetic Algorithm, Inventory Optimization, Supply Chain Management.

I. INTRODUCTION

Supply Chains are at the center stage of business performance of manufacturing and service enterprises in the recent days [1]. A SC consists of all parties involved directly or indirectly and in satisfying a customer request. It includes suppliers, manufacturers, distributors, warehouses, retailers and even customers themselves [2]. Modern supply chains are highly complex and dynamic, the number of facilities, the number of echelons, and the structure of material and information flow contribute to the complexity of the SC [3]. In addition, increases in the uncertainties in supply and demand, globalization, reduction in product and technology life cycles, and the use of outsourcing in manufacturing, distribution and logistics resulting in more complex supply networks, can lead to higher exposure to risks in the SC [4].

The ultimate goal of every SC is to maximize the overall value generated by the chain, which depends on the ability of the organization to fulfill customer orders faster and more efficiently [3]. SCM is an integrated approach to plan and control materials and information flows [5].

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Successful SCM incorporates extensive coordination among multiple functions and independent companies working together to deliver a product or service to end consumers [6]. Inventory control has been considered as a vital problem in the SCM for several decades [7].

The SC cost is hugely influenced by the excess or shortage of inventories [8]. Since inventory is one of the major factors that affect the performance of SC system, the effective reduction of inventory can substantially reduce the cost level of the total SC [9]. Thus, inventory optimization has emerged as one of the most recent topics as far as SCM is considered [8]. Under the influence of the SCM, conventional inventory control theories and methods are no longer adapted to the new environment [10]. The optimal inventory control methodologies intended to reduce the SC cost in the SC network. They minimize the SC cost by controlling the inventory in an optimal manner and so that, the SC members will not be affected by surplus as well as shortage of inventory. In order to control the inventory in an optimal manner, we propose an efficient approach with the effective utilization of data mining concepts as well as GA.

Data mining: In the current years it has seen a dramatic increase in the amount of information or data being stored in database. But, the utility of this huge data is negligible if "meaningful information" cannot be extracted from it [11]. Data mining has been emerging as an effective solution to analyze and extract hidden potential information from huge volume of data. The hidden knowledge obtained through Data mining becomes essential to support decision-making in SC tasks. [12] Usually, data mining tasks can be categorized into either prediction or description [13]. Clustering, Association Rule Mining (ARM) [14] and Sequential pattern mining are few descriptive mining techniques. The predictive mining techniques involve tasks like Classification [15], Regression and Deviation detection [16]. In this paper we considered ARM for knowledge discovery and generate the rules by applying Apriori algorithm on Inventory data. And finally attempt to optimize the generated rules by applying Genetic Algorithm.[12].

Genetic Algorithm: Genetic Algorithms first conceived by John Holland at the University of Michigan in 1975, are class of computational models that imitate natural evolution to solve problem in wide verity of domains. A Genetic algorithm is a type of searching algorithm [12]. It searches a solution space for an optimal solution to a problem. In this paper GA is used for optimal inventory control in a SC.

The organization of this paper is given as follows: In Section II Proposed model for optimal inventory control with mathematical formulations is explained. In Section III

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Implementation results of the model are discussed. Conclusions are discussed in section IV.

II. Proposed model for optimal inventory control

In the proposed model for optimal inventory control, two major functions are included, namely, association rules mining for inventory and recognizing optimal inventory rules to be maintained. Prior to perform the two aforesaid functions, a database of historical data has to be maintained. The database holds the historical record of inventory over N_p periods in N_S SC members, say, $[I_{ij}]_{N_P \times N_S}; 0 \le i \le N_P - 1$ and $0 \le j \le N_S - 1$. Initially, the Exponential Moving Average (EMA) is determined for the historical data as follows

$$I_{ema_{lj}} = I_{prev_{lj}} + \alpha(I_{(l+n)j} - I_{prev_{lj}}); \; 0 \le l \le N_P-(n+1) \quad \text{.... (1)}$$

where,

$$I_{prev_{lj}} = \begin{cases} I_{ema_{(l-1)j}} & ; if\ l > 0 \\ \frac{1}{n}\sum_{i=0}^{n-1} I_{ij} & ; otherwise \end{cases} \quad \text{......... (2)}$$

The EMA values of the original historical data for $N_P - n$ periods, $[I_{ema_{lj}}]_{(N_P-n)\times N_S}$ from Eq. (1), where, $\alpha = 2/(n+1)$ (termed as constant smoothing factor), is subjected for a decision making process as follows

$$I'_{ema_{lj}} = \begin{cases} shortage & ; I_{ema_{lj}} < I_{th} \\ balance & ; I_{ema_{lj}} = I_{th} \\ excess & ; I_{ema_{lj}} > I_{th} \end{cases} \quad \text{......... (3)}$$

As given above, EMA-based inventory data $[I'_{ema_{lj}}]_{(N_P-n)\times N_S}$ is obtained in which the original historical data is converted into three different states of inventory which include shortage, balance and excess. Subsequently, the association rules for inventory are mined from the previously obtained EMA-based inventory data.

A. Mining Association rules for inventory using Apriori

One of the two major functions of the approach, mining association rules for inventory is described in the sub-section. Mining the association rules for inventory is to find the relationship between the inventories of the SC members. In the proposed approach, we utilize Apriori, a classic algorithm for learning the association rules. Let, $\{I'_{ema_{l1}}, I'_{ema_{l2}}, I'_{ema_{l3}}, \cdots, I'_{ema_{lN_S}}\}$ be the itemset taken from the EMA-based inventory data $\{I'_{ema_{lj}}\}_{(N_P-n)\times N_S}$. The itemset and the dataset $\{I'_{ema_{lj}}\}_{(N_P-n)\times N_S}$ are subjected to Apriori for mining association rules. Initially, the Apriori finds the frequent itemsets with a minimum support threshold $s_{\min}$, and determines the rule which states the probabilistic relationship between the items in the frequent itemsets with a minimum confidence of $c_{\min}$.

The Apriori determines the association rules from the frequent itemset by calculating the possibility of an item to be present in the frequent itemset, given another item or items is present. For instance, considering a frequent itemset, $I'_{ema_{l1}}$, $I'_{ema_{l2}}$ and $I'_{ema_{l3}}$ in which a rule may be derived as when the inventory in $I'_{ema_{l1}}$ and $I'_{ema_{l2}}$ are excess in a period $l; l \in (N_P - n)$, then the inventory in $I'_{ema_{l3}}$ is likely to be shortage. The general syntax of the rule for the aforesaid example is given as $(I'_{ema_{l1}} = excess, I'_{ema_{l2}} = excess) \to (I'_{ema_{l3}} = Shortage)$; $c \ge c_{\min}$. Hence, by using the apriori, the association rules are mined with a minimal confidence $c_{\min}$ based on the frequent itemset with a minimal support $s_{\min}$. The mined rules are given as $\{A\}_q \to \{B\}_q$; $0 \le q \le N_r - 1$, where, $\{A\}_q$ and $\{B\}_q$ are the antecedent and consequent of the q^{th} rule respectively and N_r be the number of association rules generated. The antecedent and consequent consists of one or more items that belongs to the itemset $\{I'_{ema_{lj}}\}$ (i.e. $\{A\}_q \subseteq \{I'_{ema_{lj}}\}$, $\{B\}_q \subseteq \{I'_{ema_{lj}}\}$) and also it satisfies $\{A\}_q \cap \{B\}_q = \phi$. After obtaining the association rules, they are allocated for j^{th} SC member based on the consequent of the rules. The final rules after allocation are obtained as follows

$$R'_j = R_j - \phi \quad \text{............(4)}$$

where,

$$R_j = \begin{cases} \{A\}_q \to \{B\}_q; & if\ I'_{ema_{lj}} \in \{B\}_q \\ \phi & ; else \end{cases} \quad \text{......... (5)}$$

Using Eq. (5), the rules R'_j which have the element $I'_{ema_{lj}}$ in the consequent are assigned to the j^{th} SC member. Each SC member has its own rules that illustrate its inventory's state with respect to other SC member or members. So, N_S set of rules are obtained where each set has $|R'_j|$ number of rules and they need not to be in equal number. From the N_S set of rules, a rule per each SC member (i.e. a rule per set) is selected using GA. The rules are chosen in such a way that they have major impact over the SC cost.

B. Selecting SC cost-impact rules using Genetic Algorithm

The obtained rules from apriori are the frequently occurred events in the past and so they illustrate that they have a good impact over the SC cost, but not strongly. To identify the rules that have strong impact over the SC cost (SC cost-impact rules), it is essential to consider the shortage cost and holding cost. It is already known that the SC cost increases, when either of the shortage and holding costs increases. Hence, by considering the shortage or holding cost in the GA, SC cost-impact rules can be obtained. The process of selecting SC cost-impact rules using GA is explained as follows

Step 1: Generate initial chromosomes, $X_a = [x_0^{(a)} \; x_1^{(a)} \; x_2^{(a)} \; \cdots \; x_{N_S-1}^{(a)}]$; $0 \le a \le N_{pop} - 1$, where N_{pop} is the population size. The j^{th} gene of the chromosome $x_j^{(a)}$; $0 \le j \le N_S - 1$ is an arbitrary integer in the interval $(0, |R_j^{'}| - 1)$, where, $\left|R_j^{'}\right|$ is the cardinality of the rule set belongs to the j^{th} SC member.

Step 2: Determine fitness of the chromosomes present in the population pool using the fitness function

$$f(a) = \frac{1}{\sum_{j=0}^{N_S-1} \left(C_{I_j} \times \left| \mu_{ema_j}(R_j^{'}(x_j^{(a)})) \right| \times c_{R_j^{'}(x_j^{(a)})} \right)} \quad \text{.......(6)}$$

where,

$$C_{I_j} = \begin{cases} S_{c_j}; & if\ \mu_{ema_j}(R_j^{'}(x_j^{(a)})) < 0 \\ H_{c_j}; & if\ \mu_{ema_j}(R_j^{'}(x_j^{(a)})) > 0 \\ 0 \;; & if\ \mu_{ema_j}(R_j^{'}(x_j^{(a)})) = 0 \end{cases} \quad \text{.......(7)}$$

$$\mu_{ema_j}(R_j^{'}(x_j^{(a)})) = \frac{1}{F_{R_j^{'}(x_j^{(a)})}} \sum_{k \in (0, N_P - (n+1))} I_{ema_{kj}} \quad \text{....... (8)}$$

In Eq. (6), $f(a)$ is the fitness value of a^{th} chromosome, C_{I_j} (determined using Eq. (7)) is the inventory cost incurred by the j^{th} SC member, $\mu_{ema_j}(R_j^{'}(x_j^{(a)}))$ (determined using Eq. (8)) is the mean EMA value of the $I_{ema_{lj}}$ that are taken only from the pattern which satisfies the rule $R_j^{'}(x_j^{(a)})$ and $c_{R_j^{'}(x_j^{(a)})}$ is the confidence of the rule $R_j^{'}(x_j^{(a)})$. In Eq. (7), S_{c_j} is the shortage cost incurred for a unit of shortage in j^{th} SC member, H_{c_j} is the holding cost incurred for a unit to hold in the j^{th} SC member. In Eq. (8), $F_{R_j^{'}(x_j^{(a)})}$ is the frequency of occurrence of data pattern that satisfies the rule $R_j^{'}(x_j^{(a)})$ and $I_{ema_{kj}}$ is the EMA value of inventory in j^{th} SC member that are available in the data pattern, where, $I_{ema_{kj}} \in \{I_{ema_{lj}}\}$.

Step 3: Select the best $N_{pop}/2$ chromosomes, which have minimum fitness, from the population pool.

Step 4: Crossover the selected chromosomes with a crossover rate of CR so as to obtain $N_{pop}/2$ children chromosomes.

Step 5: Mutate the children with a mutation rate of MR which leads to $N_{pop}/2$ new chromosomes.

Step 6: Place the $N_{pop}/2$ new chromosomes and $N_{pop}/2$ parent chromosomes in the population pool.

Step 7: Go to step 2, until the process reaches a maximum number of iterations N_g. Once the process reaches N_g, terminate it and select the $N_{pop}/2$ best chromosomes, which have minimum fitness value.

The best chromosomes obtained from the GA indicate $N_{pop}/2$ set of rules in which each set has N_S rules (one rule per SC member). From the rule obtained for a particular SC member, it can be decided that

- The inventory will likely to be as in the rule given the inventory of the associated SC members.
- Either by reducing or by increasing the holding level of inventory (can be decided from the rule) in the SC member, an optimal level of inventory can be maintained in the upcoming days.

Hence, by the optimal inventory control, the SC member will not be suffered either by increased shortage cost or by increased holding cost. This ultimately helps to keep the SC cost in a controlled manner.

C. Evaluation of Rules

The efficacy of the rules is demonstrated by comparing the obtained rules with all the remaining rules. To accomplish this, the SC cost and the confidence of the rule associated to the best chromosome are determined as

$$SC^{best} = \sum_{j=0}^{N_S-1} \left(C_{I_j} \times \left| \mu_{ema}(R_j^{'}(x_j^{best})) \right| \right) \quad \text{........(9)}$$

$$c^{best} = \sum_{j=0}^{N_S-1} c_{R_j(x_j^{best})} \quad \text{.......(10)}$$

Similarly, the mean SC cost and the mean confidence are determined for all the remaining rules in the rule set $\{R_j^{'}\}$. Then, the efficacy is compared by determining the difference between the SC cost and confidence of the final SC cost-impact rule and the mean SC cost and the mean confidence of the remaining rules, respectively.

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IV. RESULTS AND DISCUSSION

The proposed approach for optimal inventory control has been implemented in the working platform of JAVA (version JDK 1.6) and the results are discussed in this section. The inventory data (weekly data) has been simulated for five years (i.e. $N_p = 260$) by considering five SC members (i.e. $N_s = 5$), an agent A_1 and four retailers, R_1, R_2, R_3 and R_4. In the simulated inventory data, the negative and positive values represent the shortage amount of inventory and excess amount of inventory respectively. All the SC members have been considered to have the shortage cost and holding cost as $S_c = Rs.2.50$ and $H_c = Rs.1.00$ respectively. The I'_{ema} determined from the simulated data with $n = 7$ is given in the Table I.

Table I: A sample of EMA-based inventory determined from the simulated data

Sl. No	A_1	R_1	R_2	R_3	R_4
1	Excess	Shortage	Excess	Excess	Excess
2	Excess	Shortage	Excess	Shortage	Shortage

The first major function of the proposed approach, mining association rules for inventory using Apriori has been implemented with the aid of data mining software WEKA (version 3.7). Table II and Table III consist of some frequent itemsets with $s_{min} = 10\%$ that are discovered from the I'_{ema} and some of the association rules generated from the discovered frequent itemset respectively. The rules that are categorized based on the consequent are shown in the Table IV.

Table II: Some Frequent itemsets discovered from I'_{ema} at lengths L_1, L_2, L_3 and L_4, and their support.

Length of the itemset	Frequent itemset	Support %
L_1	R_1=Shortage 0.536	53.6
	R_1=Excess 0.476	47.6
	R_2=Excess 0.6	60
L_2	R_1=Shortage, R_2=Excess 0.316	31.6
	R_1=Shortage, R_2=Shortage 0.22	22
	R_1=Shortage, R_3=Excess 0.224	22.4
L_3	R_1=Shortage, R_2=Excess, R_3=Excess 0.128	12.8
	R_1=Shortage, R_2=Excess, R_3=Shortage 0.188	18.8
	R_1=Shortage, R_2=Excess, R_4=Excess 0.132	13.2
L_4	R_1=Shortage, R_2=Excess, R_3=Shortage, R_4=Shortage 0.1	10
	R_1=Shortage, R_2=Excess, R_3=Shortage, A_1 =Shortage 0.104	10.4

Table III: Some generated association rules with $c_{min} = 30\%$ and their confidence

Sl. No	Association Rules	Confidence %
1	R_2=Excess, R_4=Shortage, A=Excess ==> R_1=Shortage	79
2	R_1=Excess, A=Excess ==> R_3=Shortage	76

Table IV: Some of the rules that are categorized based on the consequent of the rules

Sl. No	Rule for A_1	Rule for R_1	Rule for R_2	Rule for R_3	Rule for R_4
1	(R_1=Excess, R_3=Excess) → A1=Shortage	(R_2=Excess, R_4=Shortage, A1=Excess) → R_1=Shortage	(R_1=Excess, R_4=Excess, A1=Shortage) → R_2=Excess	(R_1=Excess, A1=Excess) → R_3=Shortage	(R_1=Excess, R_2=Excess, R_3=Shortage) → R_4=Excess
2	(R_2=Shortage ,R_4=Shortage) → A1=Shortage	(R_2=Excess, R_4=Shortage) → R_1=Shortage	(R_1=Excess, R_3=Shortage, R_4=Excess) → R_2=Excess	(R_1=Shortage, R_2=Excess, A1=Shortage) → R_3=Shortage	(R_2=Shortage, R_3=Excess) → R_4=Shortage

In selecting the SC cost-impact rules, the GA has been initialized with a chromosome length = 5 (i.e. $number\ of\ genes = 5$), $N_{pop} = 10$ and $N_g = 50$. The generated initial chromosome and the rules that are associated to the chromosome are given in the Fig. 1 and the Table V, respectively.

0	1	2	3	4
78	58	86	59	17

Fig. 1: An initial chromosome of length '5' with random values in their genes

Table V: The rules associated to the chromosome, which is given in the Fig. 1.

Gene. no	Associated rules
0	R_4 = -12.46 --> R_1 = -11.7, R_3 = -8.64
1	R_3 = -11.32 --> R_2 = -9.09
2	R_4 = -12.46 --> R_1 = -11.7, R_3 = -8.64
3	R_2 = -8.84 --> R_4= 6.26
4	R_1 = -11.91 --> A_1 = -45.6

The generated chromosomes have been subjected to crossover with $CR = 0.6$ and the obtained children have been subjected to mutation with $MR = 0.4$. In the mutation, the gene values in the mutation point are changed arbitrarily so that new chromosome is obtained from the child chromosome. The final SC cost-impact rules that are associated to the obtained best chromosomes are given in the Table VI.

Table VI: The final SC cost-impact rule associated to the best chromosome obtained from GA.

Solution no.	Best SC cost-impact Rule				
	A_1	R_1	R_2	R_3	R_4
1	R_4 = -11.84 → R_2 = -10.89, A_1 = -45.89	R_4 = -10.33 → R_1 = -12.02, A_1 = -46.68	R_4 = -11.62 → R_2 = -10.02	R_4 = 9.67 → R_1 = 14.12, R_3 = -12.52	R_3 = -8.55 → R_4 = -12.11

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All the obtained rules in a solution provide their combined contribution in the SC cost. The SC cost given by the solution was very high in the past records and so, by considering those rules in the solution, the SC cost can be reduced in the future. The cost reduction can be accomplished by inverse holding of inventory that has been obtained as a rule for a particular SC member. From Table VI, by keeping 46, 12, 10, 13 and 12 (approximately) units of products additionally in the SC member A_1, R_1, R_2, R_3 and R_4, respectively, the SC cost will be reduced in the future. For evaluation, the SC^{best}, c^{best} (from solution I), SC^{mean} SC mean, c^{mean} have been determined and tabulated in the Table VII.

Table VII: Comparison of the obtained SC-cost impact rule and the rest of the rules in the rule set $\{R'_j\}$ based on the SC cost and the confidence of the rule.

Sl. no.	Efficacy Factor	SC Cost- Impact rule	Rest of the Rule set $\{R'_j\}$
1	SC Cost (in Rs.)	222.50	145.40
2	Confidence (in %)	51.93	38.60

From Table VII, it can be demonstrated that the SC cost-impact rule which is obtained from best chromosome claims more SC cost as well as more frequency of occurrence rather than the all the other rules. Hence, by considering the rule, the optimal inventory can be maintained in all the SC members and so SC can be reduced effectively.

V. Conclusion

In the paper, an efficient model for optimal inventory control using Data mining Apriori algorithm and GA has been proposed and implemented. For experimentation, we have utilized the EMA-based inventory data determined from the simulated data. The results have shown that the effectual association rules are mined from the EMA-based inventory data using Apriori. Then, the rules have been categorized based on their consequent, followed by the selection of SC cost-impact rules using GA. The fitness function devised for the GA has performed well in selecting the rules that have high impact on the SC cost. It can be decided that, the upcoming inventory in any SC member will likely be as in the obtained SC cost-impact rules. It can also be decided, whether, the inventory has to be reduced or increased in the particular SC member. EMA level of inventory to be increased or decreased can also be determined from the obtained SC cost-impact rules. Thus, the SC cost will be reduced proficiently by the proposed optimal inventory control model that paves the way for effective SCM.

References

[1] Shantanu Biswas And Y. Narahari, "Object oriented modeling and decision support for supply chains", European Journal of Operational Research, vol. 153, No. 3, pp. 704-726,2004.
[2] M. Zandieh and S. Molla- Alizadeh- Zavardehi, "Synchronized Production and Distribution Scheduling with Due Window", in proceedings of Journal on Applied Sciences, vol. 8, no. 15, pp: 2752- 2757, 2008.
[3] Mustafa Rawata and Tayfur Altiokb, "Analysis of Safety Stock Policies in De-centralized Supply Chains", International Journal of Production Research, Vol. 00, No. 00, pp. 1-22, March 2008.
[4] Vasco Sanchez Rodrigues, Damian Stantchev, Andrew Potter and Mohamed Naim and Anthony Whiteing, "Establishing a transport operation focused uncertainty model for the supply chain", International Journal of Physical Distribution & Logistics Management, Vol. 38 No. 5, pp. 388-411, April 2008.
[5] Shen-Lian Chung and Hui-Ming Wee, "Pricing Discount For A Supply Chain Coordination Policy With Price Dependent Demand", Journal of the Chinese Institute of Industrial Engineers, Vol. 23, No. 3, pp. 222-232, 2006.
[6] Jennifer Blackhurst, Christopher W. Craighead and Robert B, "Towards supply chain collaboration: an operations audit of VMI initiatives in the electronics industry", Int. J. Integrated Supply Management, Vol. 2, No. 1/2, pp. 91-105, 2006.
[7] Mileff, Péter, Nehéz, Károly, “A new inventory control method for supply chain management”, 12th International Conference on Machine Design and Production, 2006.
[8] P. Radhakrishnan, V.M. Prasad and M.R. Gopalan, "Optimizing Inventory Using Genetic Algorithm for Efficient Supply Chain Management," Journal of Computer Science, Vol. 5, No. 3, pp. 233-241, 2009.
[9] Guangshu Chang, “Supply Chain Inventory Level with Procurement Constraints”, International Conference on Wireless Communications, Networking and Mobile Computing, 2007, WiCom 2007, p.p. 4931-4933, DOI. 10.1109/WICOM.2007.1208.
[10] Guangyu Xiong and Hannu Koivisto, "Research on Fuzzy Inventory Control under Supply Chain Management Environment," in proceedings of Applied Simulation and Modelling, pp. 907–916, September 3 – 5, Marbella, Spain, 2003.
[11] Yehuda Lindell and Benny Pinkas, "Privacy Preserving Data Mining", journal of Cryptography, vol. 15, no. 3,2002.
[12] Sanjeef sharma, Vivek Badhe and Sudhir sharma “Optimization of Association Rules Using Genetic Algorithms”, Int. Journal of Soft Computing, pp. 75-79, 2007.
[13] Tibebe Beshah Tesema, Ajith Abraham And Crina Grosan, "Rule Mining And Classification of Road Traffic Accidents Using Adaptive Regression Trees", In Proc. Of I. J. On Simulation, Vol. 6, No. 10 And 11, 2008.
[14] F. Coenen, Leng, P., Goulbourne, G., “Tree Structures for Mining Association Rules”, Journal of Data Mining and Knowledge Discovery, Vol 15, pp: 391-398, 2004.
[15] Hewen Tang, Wei Fang and Yongsheng Cao, "A simple method of classification with VCL components", proceedings of the 21st international CODATA Conference, 2008.
[16] S.Shankar, T.Purusothaman, “Utility Sentient Frequent Itemset Mining and Association Rule Mining: A Literature Survey and Comparative Study”, International Journal of Soft Computing Applications, ISSN: 1453-2277 Issue 4 (2009), pp.81-95