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Supplier Evaluation Model on SAP ERP Application using Machine Learning Algorithms

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Abstract

For business enterprises, supplier evaluation is a mission critical process. On ERP (Enterprise Resource Planning) applications such as SAP, the supplier evaluation process is performed by configuring a linear score model, however this approach has a limited success. Therefore, author in this paper has proposed a two-stage supplier evaluation model by integrating data from SAP application and ML algorithms. In the first stage, author has applied data extraction algorithm on SAP application to build a data model comprising of relevant features. In the second stage, each instance in the data model is classified, on a rank of 1 to 6, based on the supplier performance measurements such as on-time, on quality and as promised quantity features. Thereafter, author has applied various machine learning algorithms on training sample with multi-classification objective to allow algorithm to learn supplier ranking classification. Encouraging test results were observed when learning algorithms,(DT) and Support Vector Machine (SVM), were tested with more than 98 percent accuracy on test data sets. The application of supplier evaluation model proposed in the paper can therefore be generalised to any other other information management system, not only limited to SAP, that manages Procure to Pay process.

Keywords: *Decision Tree; ERP; HANA; Machine learning; Naive Bias; Procurement; SAP; Supervised Learning; Supplier Evaluation; Supplier Ranking; Support Vector Machine; SVM*

1. Introduction

Supplier evaluation process has gained importance since last few years even though the process is challenging and costly to perform. Setting up decision criteria and evaluation methods for supplier performance has always been a topic of interest for research practitioners [1]. The last two decades have witnessed a growth in the supply chain function wherein the activity of purchase and subsequent supplier evaluations is strongly correlated with the performance of the enterprise. Appropriate selection of suppliers is, therefore, an important prerequisite for an organization to manage supply chain successfully.

Decision making with regards to supplier selection and performance evaluation includes both quantitative and qualitative assessment factors [2] [3].

Several previous types of research have shown the use of statistical and mathematical methods for supplier evaluation. One commonly utilized method is the Data Envelopment Analysis (DEA) that can be used for the measurement of supplier efficiency and reduce the total cost of ownership [4]. A study by Hashemi, Karimi, and Tavana [5] suggested a model for supplier optimization using a hybrid approach involving a combination of Grey Relational Analysis (GRA) and Analytical Hierarchy Process (AHP).

Machine Learning (ML) is used as an alternative technique that can be applied to resolve complex classification problems. Wu [6] in a recent study proposed a hybrid model combining ML and statistical methods to evaluate suppliers. Support Vector Machine (SVM) is one important ML algorithm that is applied by vast number of researchers to resolve classification problems [7]. However, only a handful of studies have been conducted to date that have evaluated the application of SVM to perform supplier evaluation [8] [9].

The majority of small businesses [10] and large enterprises use information systems to manage their purchasing functions. Around 80 percent of fortune 1000 and 60 percent of fortune 2000 companies use SAP as their ERP tool [11] to manage processes. SAP application can successfully manage processes and offer controls in functions such as planning of product, procurement, inventory management, vendor management, customer services and so on [12]. SAP application can also manage the procurement process successfully from PROCURE to PAY; however no predictive outcome can be generated from the application that may suggest selection of supplier based on the supplier historical performance measurements.

Author has, therefore in this paper proposed a supplier evaluation model developed on Artificial Intelligence (AI) platform to resolve supplier selection dilemma. The paper list problem statement and hypothesis in section 3, data model and two stage approach to test hypotheses in section 4 and experiment results in section 5 and 6 of this paper.

The outcome of the research shows that DT and SVM algorithms are able to classify supplier rankings with more than 97 percent accuracy, allowing model to be used as a decision support system by procurement department in an enterprise.

2. Literature review

Several previous studies using decision-making models such as analytic network process (ANP), data envelopment analysis (DEA), analytic hierarchy process (AHP), simple multi-attribute rating technique (SMART) and artificial neural networks (ANN) have been carried out to perform supplier evaluation and analysis.
Ho, Xu, Dey and Prasanta [13] carried out literature review highlighting multiple relevant criteria to perform a supplier evaluation. Identification of the best method that could suit supplier evaluation is a daunting task, highly dependent on the industry sector in which an organization operates.
Many of the supplier evaluation models mentioned in research literature can be classified into four major categories namely the linear weighted models, artificial intelligence (AI) based techniques, mathematical programming models and total cost models.
In the linear weighted model, multiple criteria attributed to rank supplier can be assigned a certain weight. Supplier performance is measured as the sum of the values acquired through multiplication of the criteria and corresponding weights. This model is simple to implement but mostly depends on the judgement of an individual to select all the possible criteria and assign weights to them. The linear weighted models include Weighted point model or linear weighted mode, analytical hierarchy process (AHP), and Categorical method. On the contrary, the total cost models are completely dependent on costs wherein in addition to the product rate, the indirect cost of an item is also considered. Even in these models, the concept of subjectivity cannot be negated.
Mathematical models are used for supplier ranking or selection and are generally complex to implement and have been predominantly used to resolve allocation problems. Multi-attribute-decision-making methods include integer programming, multi-criteria programming, goal programming, linear programming, and mixed integer programming.
Methods such as neural networks, quality function deployment, analytic network process, data envelopment analysis (DEA), and fuzzy set theory are also used extensively by various researchers [14] to perform supplier evaluation. Simic et al. [15] conducted a detailed literature review on fuzzy methods used for supplier assessment and selection.
In the present paper, author has used ML and AI techniques that have been deployed in various industries to resolve classification problem but their application in the Supply Chain Management (SCM) function is limited. Real world information systems such as SAP contains supplier performance measurements that can be integrated with AI techniques to classify and rank suppliers. With the advent of SAP HANA and in-memory databases [16], a large amount of data, both master and transactional, may reside in the real time memory of SAP application for analysis and decision making. Therefore, the application of machine learning algorithms to resolve classification problems, such as in the case of supplier ranking, becomes significantly important.
A previous research carried out by Lee and Ou-Yang [17] resulted in an accurate predictive model based on artificial neural networks that could be used for acquiring supports such as bid negotiation and making recommendations during supplier negotiation process. Wu [6] further presented a hybrid model encompassing the DEA method for classification of suppliers into different clusters based on the efficiency scores. The data was used for training the model, designed combining decision tree and neural networks algorithms. The resulting model could be used to evaluate new suppliers and displayed encouraging classification results.
Kuo et al. [18] proposed a support system involving intelligent supplier decision-making units that comprised of the fuzzy neural network (FNN), quantitative factors and a decision model. In the system, fuzzy rules are generated by the FNN model proposed with the initial weights produced by the particle swarm optimization (PSO) algorithm. However, the decision integration model is devised using ANN with the back-propagation algorithm. A Fuzzy Principal Component Analysis (PCA) model proposed by Lam et al. [19] was also utilized for resolving the problems of supplier selection.
A study by Guo et al. [20] proposed a hybrid model combining support vector machine and decision tree for supplier selection problems which involve classification and feature selection.
With all these previous research examined, it can be concluded that the classification techniques using ML algorithms can be applied in the SCM function to perform supplier evaluation and facilitate supplier selection decision-making processes.

3. Research problem and hypothesis formulation

The below section lists the challenges that are faced by ERP practitioners to evaluate suppliers. The section also states hypothesis formulation and proposed alternative supplier evaluation model using AI techniques.

3.1. Research problem

SAP application offers a supplier evaluation model designed on linear scoring model in which weights are manually assigned to the evaluation criteria such as price, delivery date, quality and so on. The supplier's evaluation score is calculated as sum of the weighted scores for each of the evaluation criteria. As discussed in the literature review, the manual assignment of weights leads to supplier evaluation scores that can be inconsistent and subjective.
Also SAP and other ERP applications usually capture purchase details at line item level of purchase order and therefore necessitate to perform performance measurements at each purchase order line item level, that is not usually designed in standard SAP supplier evaluation model.
Author has therefore proposed a supplier evaluation model that encompasses features from purchase order line items and the assignment of weights to the feature are automatically calculated by learning algorithms during training of the classifier on training data set.

3.2. Hypothesis formulation

The author has hypothesized that supplier evaluation can be performed by integrating ML algorithms and supplier performance measurements on three post purchase dimensions: on-time delivery, quality and quantity commitments. To implement and test proposed hypothesis author has proposed 2 stage approach to built data model as shown in Figure 1.

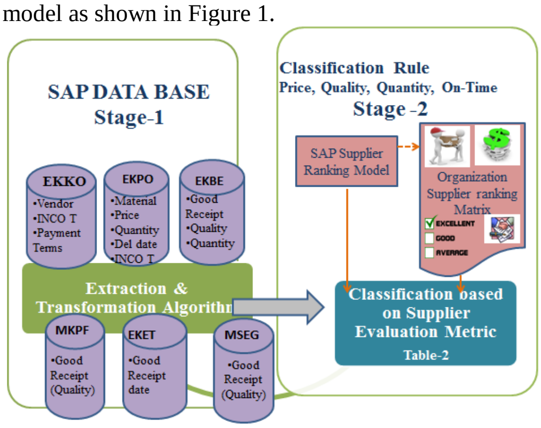

Fig. 1: Two-Stage Approach to perform supplier evaluation
Source: Author

In stage 1, set of features necessary to perform supplier evaluation are finalized. In stage 2, based on performance measurements each instance in the dataset is classified on a rank of 1 to 6. The classifier is then trained on the training sample data set and hypothesis is tested with the test data set. The detail of supplier evaluation data model and associated hypothesis test results are detailed in section 4, 5 and 6 of the paper.

3.3. Model application and benefits

The following are the main features of the supplier evaluation model:

- Iterative: The model learns with incremental data that becomes part of the SAP application over time.
- Flexible: The model can be enhanced with additional features from SAP database to evaluate supplier performance.
- Versatile: The proposed model can be extended on any other ERP or IT application.

The paper proposes a close integration between purchasing, BI (Business Intelligence) and SAP function in a business organization as shown in Figure 2. The following can be high level responsibilities of each function:

- Purchasing Department: Responsible for proposing an evaluation metric on which supplier evaluation will be performed.
- Business Intelligence: Design and build of data model, integration of SAP and ML algorithms using web services, extractors or remote function calls (RFC).
- SAP Application: Purchasing department can use the finalized data model as decision support system, to award a contract to a supplier based on the evaluation results.

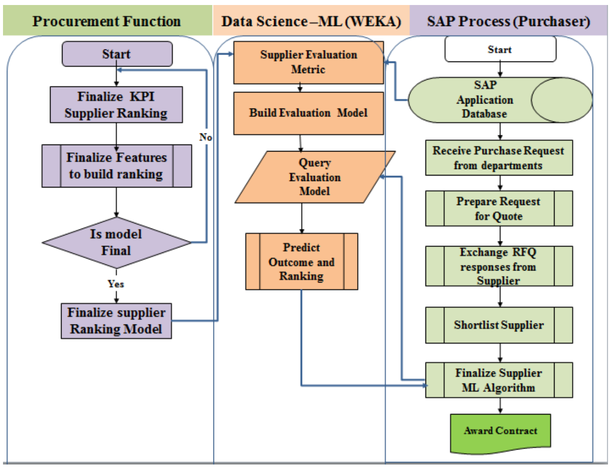

Fig. 2: Supplier Evaluation Model - Multiple Functions
Source: Author

4. Data model and feature finalization

In the paper, the author has used a two-stage approach to build a decision support data model from the SAP application as shown in Figure 1.

The following steps were carried out in stage-1.

- Using inputs from industry experts and literature reviews, author has finalized set of features (Table 1) useful to perform supplier evaluation.
- Used data extraction algorithm to build a data model.
- Calculated supplier performance measurements against contractual commitments; on-time, on quality, and on quantity dimensional parameters.

During stage 2, each instance in the data model is classified with a rank based on the supplier performance measurements and evaluation matrix defined in Table 2. Thereafter, various ML algorithms were trained and tested to evaluate the classification performance of the model.

Table 1: Data Model: Features Used for Supplier Evaluation

Feature	Feature description
Supplier	Supplier code from SAP (EKKO), *Attribute-Nominal*
Material Group	High level code on which purchasing reports in SAP are executed. For example hard drive, monitors, mother boards and so on (EKPO), *Attribute-Nominal*
Material Number	Material number that is unique for an item in SAP (EKPO), *Attribute-Nominal*
Purchase Org.	The Legal entity in SAP that is performing the purchase (EKKO), *Attribute Nominal*
Inter-country Purchase	Binary feature to distinguish same country (Intra) and different country purchase (Inter) *Attribute-Binary*
Quantity	Quantity purchased for each Purchase Order line item. (EKPO), *Attribute-discrete in 10 bins*
Gross Price	Total Amount of purchase for a PO line item. (EKPO), *Attribute-discrete in 10 bins*
INCO Terms	A purchasing condition agreed between supplier and buyer goods (EKPO), *Attribute-Nominal*
Rebate	Rebate offered at PO Line item level (percentage terms) (EKPO), *Attribute-discrete in 10 bins*
Payment Terms	Terms of payment agreed between Buyer and Supplier for a PO (EKKO), *Attribute-Nominal*
Agreement	Purchase is carried out based on an existing contract or a standalone purchase (EKPO), *Attribute-Binary*
ConQty	Quantity received by the buying organization at PO line item level as per contract (Y/N) *Attribute-Binary*
Dev2	Deviation in % terms on the quantity ordered and not received, *Attribute-discrete in 10 bins*
ConDeIT	On time delivery of Purchase order line item as per contractual delivery date (Y/N), *Attribute-Binary*
Dev1	Deviation was calculated in number of days the delivery was late (EKPO, EKBE), *Attribute-discrete in 10 bins*
ConQual	On Quality delivery of Purchase order line item, check returns and movement types (Y/N), *Attribute-Binary*
Dev3	In % terms quantity received not adhering to quality (returns or blocked), *Attribute-discrete in 10 bins*
Classification	A rank assigned to each instance based on the evaluation metric specified in Table 2.

Table 2: Supplier Evaluation Metric Classification

		Evaluation Criteria On time (Days), Quantity & Quality (% of Purchase Order (PO) Quantity)			
Class	Instances	On Time	Quantity	Quality	Deviation Criteria
1	384	Y	Y	Y	No deviation
2	722	<10 Days	Y	Y	Delay of 10 days or less
3	551	10-30 Days	<10% of PO Qty	<10% of PO Qty	Any one dimension
4	634	>30 Days	>10% of PO Qty	>10% of PO Qty	Any one dimension
5	12	>30 Days	>10% of PO Qty	>10% of PO Qty	Any two dimensions
6	0	>30 Days	>10% of PO Qty	>10% of PO Qty	All three dimensions

Source: Author, based on Industry Experts

4.1. Stage-1 data extraction and transformation

Using rules specified in Algorithm 1, author has extracted historical data for set of features (Table 1) for those purchase orders that have delivery and invoice process completed. Each instance in the final data model is extracted from Purchase order header (EKKO), line item (EKPO) or history table (EKBE and EKET) fields with primary key as purchase order number. The data extraction was performed from SAP IDES application. SAP IDES is a dummy SAP instance that is usually used for demo and training purpose.

Algorithm 1: Data Extraction Algorithm

Data: *tableEKKO*(*POHeader*) *EKPO*(*POItem*) *EKBE*, *EKET*(*History*)
Result: Data Model to perform Supplier Evaluation
Table perform selection initialization
// Step to extract contractual details of purchase order
while *Select All From EKKO where EKKO- BSTYP= F and EKKO-BSART NE UB, ZUB, ZTUB (Ignore Intercompany ans Intracompany Purchase Orders* **do**
if *EKPO-LOEKZ NE X (Item is not deleted) and EKPO-ELIKZ=X (Delivery is completed) and EKPO-ERKEZ=X (Final Invoice is raised)* **then**
select all entries from Purchase order Line (EKPO) and header (EKKO) tables
Select all the entries from table EKBE with Primary Key as (EKBE-EBELN) and line item (EKBE-EBELP)
Select Material document (EKBE-BELNR), movement type (EKBE-BWART), date of reception (EKBE-BLDAT) and quantity (EKBE-MENGE)
// Perform supplier evaluation by measuring supplier performance against a contract
Dev1- Perform *(EKBE-BDWAT)-(EKET-EINDT) Calculate Deviation between last good receipt date and PO contractual delivery date*
Dev2- Perform *(EKPO-Menge)-Σ(EKBE-MENGE) Calculate deviation between ordered quantity and quantity received*
Dev3- *(EKPO-Menge)-Σ(EKBE-Menge)* where (EKBE-BWART) NE 101: *Calculate quantity not received as per quality parameters and calculate deviation with ordered quantity*
Get additional quality details from table MSEG and MKPF (Returns)
end
/* iterate over all examples */
Exit
end

The finalized data model with its list of features is detailed in Table 1. Usually, the features such as price, rebate, INCO terms are finalized with a supplier before a purchase order is placed. Therefore, the author's objective was to measure contractual deviations for a supplier on time, quantity and quality parameters and measure and evaluate supplier performance.

4.2. Dataset classification using evaluation metric- Stage 2

For instances finalized in the dataset from stage-1, author has used a supplier evaluation metric specified in Table 2 to classify each instance. The evaluation metric specified in Table 2 was developed using inputs from industry experts. Each instance in the data model was classified and assigned a rank from 1 to 6 based on observed deviations for quantity, quality, and on-time delivery performance measurements baselines, also referred as dimensions, against evaluation metric listed in Table 2. The metric specified in table 2 can be fine-tuned and incorporated with additional evaluation criteria if needed.

4.3. Data cleaning and finalization

The dataset prepared post completion of stage 1 and 2 consisted of 2303 instances for 140 suppliers including 17 features. The classification distribution for the instances is listed in Table 2. This data was split 75 percent into the training set (n=1727) and 25 percent into test set (n=576) using WEKA resample filter with Invert selection and No replacement filter settings. The feature of each attribute is highlighted in italics in Table 1.

5. Experiment results – Implementation of machine learning algorithms

Various supervised ML algorithms were trained using 10 Fold and 30 fold cross-validation on the training data set and the model was tested with the test data set using WEKA ML tool. For the sake of negating bias and variance; bagging, boosting and stacking ensemble methods were used by researchers and the results were recorded.

5.1. Experiment results- Application of machine learning algorithms on dataset

According to Salzburg [21], cross-validation is an effective method to reduce data dependency and improve the reliability of the classifier results. Each ML algorithm during training was subjected to 10 and 30 fold cross-validation to ensure generalization and avoid over-fitting. Author has applied Naïve Bias, Decision Tree, KNN, SVM, and Logistic regression algorithms on the training data set and tested the learning algorithm on the test data set. The results recorded are listed in Table 3 for the training sets and Table 4 for the test sets detailing accuracy, precision, recall, true positive rate (TPR) and F-score for each algorithm.

Table 3: ML algorithm implementation results – training dataset

Algorithm	Accuracy	Precision	Recall	F-measure	TPR
NB (CV 10 Fold)	90.8512	0.914	0.909	0.908	0.909
NB (CV 30 Fold)	90.967	0.915	0.91	0.909	0.91
DT (CV 10 Fold)	98.0892	0.981	0.981	0.981	0.981
DT (CV 30 Fold)	98.08	0.981	0.981	0.981	0.981
KNN (CV 10 Fold)- K=1	94.03	0.941	0.94	0.94	0.94
KNN (CV 10 Fold- K=20	91.6	0.913	0.916	0.914	0.916
SVM (CV 10 Fold)	97.85	0.979	0.979	0.979	0.979
SVM (CV 30 Fold)	97.85	0.979	0.979	0.979	0.979
LR (CV 10 Fold)	95.13	0.951	0.952	0.952	0.964
LR (CV 30 Fold)	96.29	0.963	0.962	0.962	0.963

Table 4: ML algorithm implementation results – test dataset

Algorithm	Accuracy	Precision	Recall	F-measure	TPR
NB (CV 10 Fold)	91.14	0.918	0.911	0.911	0.911
NB (CV 30 Fold)	91.14	0.918	0.911	0.911	0.911
DT (CV 10 Fold)	97.22	0.973	0.972	0.972	0.972
DT (CV 30 Fold)	97.22	0.973	0.972	0.972	0.972
KNN (CV 10 Fold)- K=1	93.22	0.933	0.932	0.932	0.932
KNN (CV 10 Fold- K=20	91.31	0.912	0.913	0.912	0.913
SVM (CV 10 Fold)	97.91	0.98	0.979	0.979	0.979
SVM (CV 30 Fold)	97.91	0.98	0.98	0.98	0.979
LR (CV 10 Fold)	95.13	0.951	0.952	0.952	0.951
LR (CV 30 Fold)	95.13	0.951	0.952	0.952	0.951

The observed results showed that Decision tree, SVM, and LR classified both training and test data sets with accuracy rate of more than 96 percent. Based on the results, it can be safely concluded that LR, SVM, and Decision tree are suitable for performing supplier classification. However, to negate bias and variance factors, author has implemented ensemble methods that are detailed in the next section of the paper.
The results for test results of classification models using various ML algorithms is also shown in Figure 3.

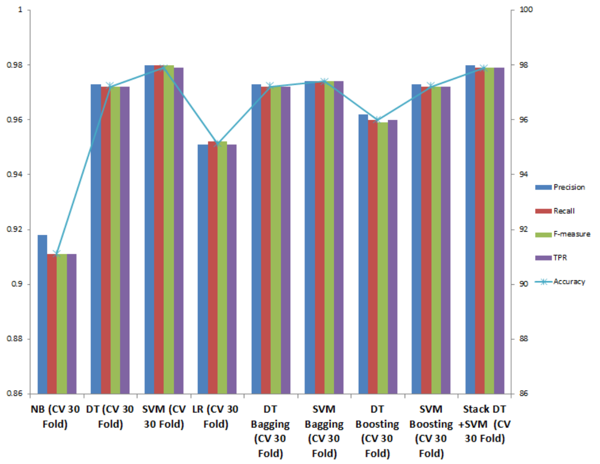

Fig. 3: Test Results Various ML Algorithms

6. Ensemble methods: Bias and variance observance

Even though author observed the high accuracy of test results, application of ensemble methods was chosen to negate any effect of bias and variance. Ensemble methods are learning algorithms wherein multiple models are combined to acquire better prediction accuracy. Breiman [22], in this regard, relates the methods as perturb and combine (PandC) wherein regression or classification model is applied to diverse dataset perturbations and the end results are integrated so as to acquire a single classifier as a model for regression.
In the present paper, bagging, boosting and stacking algorithms are used for building a predictive model using both SVM and Decision tree with 10 fold cross validation. The bagging technique builds multiple models independently by using sample data sets drawn randomly with an objective to decrease variance. However, boosting adds new model incrementally to the classifier with an objective to decrease bias. The stacking technique was also used by author where SVM and decision models were combined together for better prediction and classification.
The test results for boosting, bagging and stacking techniques are listed in Table 5 that suggest that SVM and Decision Tree are appropriate methods to perform complex classification tasks leading to successful classification of suppliers.

Table 4: ML algorithms implementation results – ensemble methods

Algorithm	Accuracy	Precision	Recall	F-measure	TPR
DT Bagging (CV 30 Fold)	97.22	0.973	0.972	0.972	0.972
SVM Bagging (CV 30 Fold)	97.4	0.974	0.974	0.974	0.974
DT Boosting (CV 30 Fold)	96	0.962	0.96	0.959	0.96
SVM Boosting (CV 30 Fold)	97.22	0.973	0.972	0.972	0.972
Stack DT +SVM (CV 30 Fold)	97.91	0.98	0.979	0.979	0.979

7. Conclusion

The present paper proposes a supplier performance evaluation model using supplier historical performance measurement data taken from the SAP application. Author has selected set of features and thereafter classified each instance in the datamodel on a rank from 1 to 6 based on supplier post-purchase performance measurements such as on-time, on quality, and on quantity deviations. The classifier model was trained on training sample data set and was subsequently tested on the test data set. To negate Bias and variance; bagging, boosting and stacking ensemble techniques were applied and results were recorded. The test results showed that DT and SVM algorithms were able to successfully perform supplier ranking classification, with ensemble method or otherwise, with more than 98 percent accuracy. The research focus of the present paper is to perform supplier evaluation using historical data available in the information system, however it is recommended to carry out further research to perform supplier evaluation using AI technique based on review of the suppliers available on social media as well.

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References

[1] Hemalatha S, Babu GR, Rao KN & Venkatasubbaiah K, "Supply Chain Strategy Based Supplier Evaluation-An Integrated Framework," *International Journal of Managing Value and Supply Chains (IJMVSC)*, Vol.6, No.2, (2015).
[2] Bevilacqua M, Ciarapica F & Giacchetta G, "A Fuzzy-QFD approach to Supplier Selection," *Journal of Purchasing and Supply Management*, Vol.12, No.1, (2006), pp.14–27.
[3] Chen CT, Lin CT & Huang SF, "A Fuzzy Approach for Supplier Evaluation and Selection in Supply Chain Management," *International Journal of Production Economics*, Vol.102, No.2, (2006), pp.289–301.
[4] Songhori MJ, Tavana M, Azadeh A & Khakbaz MH, "A Supplier Selection and Order Allocation Model with Multiple Transportation Alternatives," *The International Journal of Advanced Manufacturing Technology*, Vol.52, No.1, (2011), pp.365–376.
[5] Hashemi SH, Karimi A & Tavana M, "An Integrated Green Supplier Selection Approach with Analytic Network Process and Improved Grey Relational Analysis," *International Journal of Production Economics*, Vol.159, (2015), pp.178–191.
[6] D. Wu, "Supplier Selection: A Hybrid Model Using DEA, Decision Tree and Neural Network," *Expert Systems with Applications*, Vol.36, No.5, (2009), pp.9105–9112.
[7] Raja SDM & Shanmugam A, "ANN and SVM Based War Scene Classification Using Invariant Moments and Glcm features: A Comparative Study," *International Journal of Machine Learning and Computing*, Vol.2, No.6, (2012), p.869.
[8] Hsu C, Chang B & Hung H, "Applying SVM to Build Supplier Evaluation Model-Comparing Likert Scale and Fuzzy Scale," in *Industrial Engineering and Engineering Management, 2007 IEEE International Conference on IEEE*, (2007), pp.6–10.
[9] Dingledine R & Lethin R, "Use of Support Vector Machines for Supplier Performance Modeling."
[10] Kocaoglu B & Acar AZ, "Process Development in Customer Order Information Systems to Gain Competitive Advantage: A SME Case Study," *International Journal of Logistics Systems and Management*, Vol.23, No.2, (2016), pp.209–230, available online: http://dx.doi.org/10.1504/IJLSM.2016.073968
[11] Sand M & ERP T Share by Fortune 2000 companies, year = 2017, url = http://erp.mst.edu, urldate = 2017-02-02.
[12] Magal SR & Word J, *Integrated Business Processes with ERP Systems*. Wiley Publishing, (2011), pp.1-384.
[13] Ho W, Xu X & Dey PK, "Multi-Criteria Decision Making Approaches for Supplier Evaluation and Selection: A Literature Review," *European Journal of Operational Research*, Vol.202, No.1, (2010), pp.16–24.
[14] Keskin GA, I˙lhan S & zkan CO, "The Fuzzy Art Algorithm: A Categorization Method for Supplier Evaluation and Selection," *Expert Systems with Applications*, Vol.37, No.2, (2010), pp.1235–1240.
[15] Simi´c D, Kovaˇcevi´c I, Svirˇcevi´c V & Simi´c S, "50 Years of Fuzzy Set Theory and Models for Supplier Assessment and Selection: A Literature Review," *Journal of Applied Logic*, (2016).
[16] Plattner H & Leukert B, *The in-memory revolution: how SAP HANA enables business of the future*. Springer, (2015).

[17] Lee CC & Ou-Yang C, "A Neural Networks Approach for Forecasting the Suppliers Bid Prices in Supplier Selection Negotiation Process," *Expert Systems with Applications*, Vol.36, No.2, (2009), pp.2961–2970.
[18] Kuo R, Hong S & Huang Y, "Integration of Particle Swarm Optimization-Based Fuzzy Neural Network and Artificial Neural Network for Supplier Selection," *Applied Mathematical Modelling*, Vol.34, No.12, (2010), pp.3976–3990.
[19] Lam KC, Tao R & Lam MCK, "A Material Supplier Selection Model for Property Developers Using Fuzzy Principal Component Analysis," *Automation in Construction*, Vol.19, No.5, (2010), pp.608–618.
[20] Guo X, Yuan Z & Tian B, "Supplier Selection Based on Hierarchical Potential Support Vector Machine," *Expert Systems with Applications*, Vol.36, No.3, (2009), pp.6978–6985.
[21] Salzberg SL, "On comparing classifiers: Pitfalls to Avoid and A Recommended Approach," *Data Mining and Knowledge Discovery*, Vol.1, No.3, (1997), pp.317–328, https://doi.org/10.1023/A:1009752403260
[22] Breiman L, "Arcing Classifier (With Discussion and a Rejoinder by the Author)," *The Annals of Statistics*, Vol.26, No.3, (1998), pp.801–849.