Advanced Technology and Future Directions for Supplier Selection

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Abstract. As the supply chain system matures, the supply chain organization spends a lot of resources and manpower on supplier selection and management through tendering and negotiation. This paper describes Multi-auction Mechanism and Verizon's advanced technology VSRT to supplier screening to explore the logic of efficient, correct supplier management and the future direction of SRM based on related literature. The result shows that while both approaches offer capabilities not available in most SRMs on the market, they both provide strong data-level support for strategic decisions and help companies make decisions that are more beneficial to them. A disciplined, predictive online Supplier Relationship Management (SRM) is necessary to help companies manage supplier performance quickly and produce high-quality reports. It also provides a practical way of thinking about the future direction of SRM systems and supplier selection and technological innovation. Good updated technical support for future SRM system operation and iterative processes in enterprises.

Keywords: Supply chain, Supplier relationship management, Spend Analytic, Machine Learning, Artificial Intelligence

1 Introduction

Because of the current development of the manufacturing industry, many medium and large companies are developing various businesses in various fields (e.g., electronic technology, mechanical, optical, medical, and so on). This brings the company into contact with a wide range of suppliers to provide the materials they need for product development and mass production. At the same time, the company needs to tender and evaluate the performance of its suppliers and spend a lot of effort on supplier management or supply chain operations. In this process, the company needs to analyze thousands of supplier business attributes, which provides an excellent arena for current advanced data analysis technology to transform this process from a traditional, manual decision-making process to an intelligent, data-oriented modeling system. This is the primary function of Supplier Relationship Management (SRM), which enables buyers

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to efficiently evaluate suppliers and provide information on the status of specific operations, thereby reducing their workload and the likelihood of errors.

However, most companies' SRM modules only reflect the role of information statistics and do not manage to provide direct and effective theoretical support for recommending and implementing IT solutions for business strategies.

Some of the top companies and teams have been looking at ways to leverage current technology to enable SRM systems to achieve their mission. Verizon [1], for example, uses advanced machine learning models to downscale data and calculate industry-standard values through DEA algorithms to help companies better manage their suppliers. Yoon et al. [2] also try to add procurement category-level expertise to supplier risk management concepts. Rao et al. [3] transform risk categories from linguistically ambiguous variables to quantifiable data.

This paper will present two different approaches to vendor selection and arrangement, providing a technical direction and future perspective on SRM systems in the current market. The existing literature on supplier selection has rarely addressed the risk component, or has only involved qualitative analysis and has not quantified supplier efficiency indicators, and the linguistic fuzzy variables and information asymmetry in the quantification process have led to existing supplier selection methods (e.g., integrated fuzzy TOPSIS [4]) not being very effective. This study, therefore, seeks to systematically summarize the recent excellent papers on supplier selection and discuss in depth the advanced methods used in their studies of better SRM systems, to provide a clear and systematic way of thinking for future companies when developing SRM systems; and to provide an innovative direction for those who operate and iterate on SRM systems.

2 Related concepts

Supply Chain Management: Customers, suppliers, processes, products, and the various resources that have an impact on products and services are all part of the supply chain, which emphasizes the processes and relationships between companies. Supply chain management produces two effects through its five main functions, namely planning, buying, manufacturing, moving, and selling: reducing costs and adding value. Specifically.

-Improving strategic, operational, and financial performance within the supply chain.

-Reducing costs and effectively managing working capital.

-Efficient management of raw materials, work in progress, and finished goods in stock.

-Reducing transaction costs and improving the efficiency of transactions between supply chain members.

-Adding value to customers, providing products and services that customers want, and offering packaged solutions.

-Enhancing the ability to balance supply and demand.

Supplier selection: Supplier selection involves a continuous cycle of the business from identifying requirements to finalizing the supplier and evaluating the supplier.

3 Two-stages Compound Mechanism

Two-stages Compound Mechanism [2] is used to analyze the consideration and merit selection of possible risks for each supplier in supplier tendering.

This paper quantifies the underlying information and the various types of risk (technology risk, information risk, etc.) of supplier efficiency indicators using detailed definitions and separates the quantifiable underlying information (quality, price per unit (PPU), delivery time, delivery quantity) from the linguistically ambiguous information (various types of risk), using different architectures for evaluation and selection to form a two-stage composite mechanism. At the same time, the authors have made the procurement mechanism for homogeneous divisible items public and set up corresponding incentives to make the suppliers disclose their actual costs correctly, reduce information asymmetry, and increase the correctness and tolerance of the evaluation.

3.1 Multi-auction Mechanism

The Multi-auction Mechanism uses four precise numerical attributes (PPU, delivery time, quality, and quantity) to evaluate and select suppliers in a tender. The evaluation equation is derived as follows.

For each supplier, the revenue per unit of material is derived as PPU and the expenditure per unit of material can be summarized as $\mathrm{f(x) = (quality, delivery\_time}$, a function that increases with quality and decreases with time. So the total profit of the supplier can be calculated as $\mathrm{g(x) = quantity \times (PPU - f(x))}$. That is, the supplier's profit decreases as quality increases and increases with time.

For the purchaser, it is assumed that the purchaser's revenue function is related to the quality of the material and the delivery time. The function can then be summarized simply as $\mathrm{h(x) = quantity \times ((\sum quality + delivery\ time) - price)}$. This function decreases with time, as delivery time is a cost type attribute of the purchaser.

At this point, the purchaser can easily publish specific scoring rules on the tender and ensure that all supplier information is kept confidential, prompting suppliers to publish their own actual costs truthfully in order to maximize their benefits. This acts as an information incentive.

3.2 Multi-attribute Decision Making Mechanism

In the second stage, the authors quantified the linguistic fuzzy variables and transformed them into interval numbers, which were combined with the original four quantified attributes to transform them into a new decision matrix. The final winner is determined by comparing the actual benefit scores of each supplier through a grey correlation ranking method based on a hybrid sequence. The quantitative definitions of the seven fuzzy variables are summarized in Table 1.

Table 1. Definitions of fuzzy variables

Supply Chain Risks	Evaluation Function
Technology Risk	New productions sale/ Total sales
Information Risk	Test the efficiency of suppliers' information management systems and information sharing mechanisms
Management Risk	Number of managers with a masters' degree and above/general managers
Economic Risk	Testing of economic growth rates, market conditions, infrastructure and development prospects
Environmental Risk	Testing if there have been any major natural disasters in the last three years and if the supplier have preventive and emergency measures in place
Societal Risk	Testing the adequacy of the supplier's local legal system
Ethical Risk	Testing the supplier's reputation and timely delivery

All testing can be converted to Potential, High, Medium, or Low to evaluate the indicator. Potential = [0.9,1], High = [0.7,0.9], Medium = [0.5,0.7], Low = [0.2,0.5]. Then, after converting all risk attributes of individual suppliers into quantifiable values or intervals, the authors used the grey correlation degree to rate all suppliers. grey correlation degree is the degree of correlation between the comparison series (i.e. the supplier evaluation data from the tender) and the reference series(i.e. the most desirable data from the criteria). grey correlation degree to evaluate and rank the reference series. The definition and derivation of the optimal data can be found in that paper. Ultimately, this Two-stages Compound Mechanism approach is used to select the right supplier and seek the highest return for both the company and the supplier in order to achieve a win-win situation.

4 VSRT

The Verizon Supplier Rationalization Tool (VSRT) is Verizon's approach to rationalizing the tail end of its supplier pool. It uses advanced machine learning models, natural language processing, and artificial intelligence to save millions of dollars in business expenses and provide the best PPU for sourcing materials and products internally, facilitating better quality of service and more reasonable pricing standards for existing and potential future suppliers, helping the company to reduce overheads and be more transparent in management of systems and processes.

The main stages and functions of VSRT, illustrated in Figure 1, can be summarized as:

- Using Artificial Neural Networks (ANN) to structure internal supplier data and normalize external supplier data;
- Transformation of data by Natural Language Processing (NLP) [5] and classification of different supplier types by two parts of machine learning models;

- Evaluation and ranking of suppliers using Mixed Integer Program (MIP) and TOPSIS;
- Visualize results and provide theoretical support for business strategy;

Data Model	Machine Learning Model	Optimize Model	Visualization
Structuring internal supplier data	Artificial Neural Network Identify patterns, predict missing information	Mixed Integer Program Ranking suppliers based on performance	Real Time In-Memory Processing
Normalize external supplier data	Natural Language Processing Transforming plain text data into machine readable format	Multi Criteria Decision Making Prioritizing suppliers	
	Mixed Principal Component Dimensionality reduction		
	K-Means Clustering suppliers into groups		

Fig. 1. Models used in VSRT

4.1 Data Model

VSRT uses internal data sources and some external data sources to set up the basic data architecture. For internal data sources, Verizon (this can be extended to major medium to large enterprises) uses unstructured data such as Purchasing Order (PO) and invoice line data from Enterprise Resource Planning (ERP). This data is used because it is intuitive enough for people to see and is the most straightforward way that purchasers can upload data, reducing the amount of information missing due to errors in uploading by people. However, this is not interpretable for computers, and some of the data and criteria may be missing or mislabeled. So, NLP is needed to mark PO and invoice line data to extract the key data for each form.

The results of the text mining using NLP were then applied to a set of Verizon's own RNNs (building by Python 3.6[6]) to predict spend categories or to re-tag features when the internal data source was changed, and the RNNs were iteratively trained on the existing high-quality data set until the prediction accuracy was 98%.

For external data sources, Verizon selected known structured spend data to build the vendor's Business Attributes Matrix (BAM), which was used to optimize the overall data model. Because there are certain situations where internal vendor characteristics show some unhealthy trend (e.g. generally long or short cycles), the trained model can lead to an incorrect result in the absence of external data support.

4.2 Machine Learning Model

The machine model for VSRT is divided into two components: Mixed Principal Component Analysis (MPCA) [7], which reduces the dimensionality of highly sparse, high-latitude data, and the K-Means algorithm [8], which is used for classification.

Suppose there are K tail vendors in the vendor pool, each consisting of M business attributes, corresponding to N purchasing requirements for Verizon. The BAM in the training set would then exist with K rows and (M x N) columns. On top of this, if there is a need to combine the performance attributes of suppliers, the size of this matrix grows exponentially. Moreover, in a medium to large enterprise, there will be thousands of suppliers in the supplier pool, corresponding to many sourcing requirements, and each requirement is relatively independent of the other. So the size and density of the training set are unacceptable to traditional machine learning algorithms, and therefore require dimensionality reduction with specific algorithms.

There are algorithms suitable for this, such as factorization machines [9] but they are more difficult to implement and can be more labour-intensive; decision tree construction algorithms [10] are also a good option, as they can find a suitable branch of decision for the company itself through the experience of its own purchasing department. Again, however, this approach can be influenced by the team's own experience, resulting in biases that also come up later in the optimization model, as outlined in the next section. Ultimately, mixed principal component analysis was the solution chosen by Verizon to reduce the dimensionality of the matrix.

Once the training set has been dimensioned down, the data can be classified using the K-Means clustering algorithm. The reason for classifying the data is that it is clearly wrong to assess the same metrics for different types of suppliers. K-Means is a simple and easy-to-implement algorithm for classifying data by calculating the Euclidean distance between each pair. It is very suitable for highly sparse data.

4.3 Optimization Model

The process of optimizing the model is to take known well classified data and evaluate it, summarizing an objective criterion that applies to all data of that type. This metric is then used to examine and evaluate individual suppliers, calculate a specific score and rank them. Finally, suppliers are selected and evaluated based on the results obtained for day-to-day transactions.

Scoring the efficiency of suppliers is a bit of a balancing act. If you rely too heavily on the procurement team for evaluation, the results are limited by their experience and subjectivity, resulting in inefficient and meaningless discussions. If you rely too heavily on the evaluation criteria, you are not assessing the material requirements correctly for different priorities, and the evaluation criteria for major materials and auxiliary materials are not the same. Therefore, Verizon opted for data envelopment analysis (DEA) [11], a coordinated optimization technique that focuses on the data itself, extracting a reasonable evaluation criterion from the given data, thus eliminating the errors caused by manual analysis and calculating the appropriate criteria for each attribute. It is also possible to calculate the appropriate criteria for each attribute.

Once the DEA results have been obtained, they can be taken into the TOPSIS algorithm for scoring and prioritizing the efficiency of each supplier, which is a similar algorithm to K-Means in that it calculates the ratio of the Euclidean distance of each data item to its optimal and worst solution to obtain a score in the [0,1] range and to rank them. The result is then used by the purchasing department to provide guaranteed data to support the strategic decisions of the company.

5 Discussion

For Verizon, VSRT has saved the business ten million dollars and has provided the most profitable and effective PPU for the products the business needs to purchase, but both methods have their own problems.

For the Two-stages Compound Mechanism, the quantitative details are independent of each bid and are not referenced individually. Moreover, the validity of the method is based on all suppliers being honest about their specific information (down to a specific value) and having a reliable source of information on the risk factor for each supplier, but in practice, this is difficult to obtain reliable sources of information. For supplier-based information, even if incentives were put in place to promote the publication of truthful information by suppliers, the asymmetry of the information does not allow everyone (manager, purchasing team) to conclude that the information is sufficiently reliable. For the risk factor, the definition of the risk factor is based on the fact that both parties have already traded or are aware of the supplier's record of trading with other companies. However, this type of information is often very difficult to obtain, as it is confidential information for any company, and it is not acceptable for information to be leaked. Therefore, in practice, it is difficult to achieve significant improvements due to the difficulty of accessing information and the credibility of the method.

For VSRT, the DEA algorithm, while not limited by attribute labels (the algorithm calculates an objective assessment criterion from input data only, thus free from the bias introduced by artificially established criteria), is instead limited by the input data of the algorithm itself. That is, the objective indicators currently derived by the algorithm can only be assessed against objective criteria for the current or future period. If a major partial market shock occurs in the future (e.g. the impact of the COVID-19 epidemic) or with the passage of time, the results will no longer be valid and may even point to an incorrect outcome. Also, the algorithm needs to be recalculated once after each cycle or when one of the above contingencies occurs. This approach is undoubtedly more resource-intensive than the approach of adding a new training set to the original training model. Again, if this shortcoming can be addressed in the future, it could further save operational costs in terms of computing and management.

6 Conclusion

In this thesis, the current approaches to supplier selection and management have been described and analyzed for the strengths and weaknesses of each. Based on this analysis, although both approaches can provide functionality that most SRMs on the market do not, they can also provide strong data-level support for strategic decisions and help companies make decisions that are more beneficial to them. In the relative future, if these issues can be further addressed, they could help companies save some of their effective management expenditure. Supplier selection is currently still limited by the enterprise's own supplier pool. Due to data silos, supplier efficiency metrics are difficult to fix and quantify, so the calculated supplier efficiency metrics need to be updated regularly, which is a huge and cumbersome overhead for the system itself. In the future, the SRM system could include quantitative criteria for time, incidents, characterization of non-technical attributes (e.g., COVID-19 2020), and assessment of their impact, effectively reducing the cost of system maintenance and iteration and helping the business to reap more benefits.

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