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Clustering and selecting suppliers based on simulated annealing algorithms

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ABSTRACT

This study proposes two optimization mathematical models for the clustering and selection of suppliers. Model 1 performs an analysis of supplier clusters, according to customer demand attributes, including production cost, product quality and production time. Model 2 uses the supplier cluster obtained in Model 1 to determine the appropriate supplier combinations. The study additionally proposes a two-phase method to solve the two mathematical models. Phase 1 integrates *k*-means and a simulated annealing algorithm with the Taguchi method (TKSA) to solve for Model 1. Phase 2 uses an analytic hierarchy process (AHP) for Model 2 to weight every factor and then uses a simulated annealing algorithm with the Taguchi method (ATSA) to solve for Model 2. Finally, a case study is performed, using parts supplier segmentation and an evaluation process, which compares different heuristic methods. The results show that TKSA + ATSA provides a quality solution for this problem.

1. Introduction

Global competition means that companies must integrate with upstream and downstream supply chain partners efficiently to increase market opportunities and competitiveness and to adapt to rapid changes in market trends and customer demands. To satisfy customer demand and to lower internal cost and risk, companies select appropriate suppliers to make more competitive products and distribute these products to customers, according to the varied demands of those customers. Nonetheless, for a supply chain with a large number of suppliers, each supplier has a different product strategy and therefore a different level of competitiveness and customer demands are varied, in accordance with their preferences. If customer demand is not considered, then product types that are incompliant with customer expectations are produced, causing members of the supply chain system to suffer great losses. He et al. [1] mentioned that good supply chain management requires that companies select appropriate suppliers, according to the nature of the product purchased and the upstream market. Sun et al. [2] pointed out that the process of supplier evaluation is a process where both parties seek optimally balanced decisions in accordance with actual supplier manufacturability and serviceability. Appropriate incentives or punishments ensure a win–win situation for both parties.

Wang and Wang [3] suggested that cluster analysis could be used to cluster all suppliers and to establish a supplier evaluation index, to effectively manage suppliers. Bottani and Rizzi [4] pointed out that suppliers with similar characteristics could be clustered by using cluster analysis to reduce supplier combinations. Sung and Ramayya [5] stated that cluster analysis could effectively differentiate supplier types. Therefore, this paper proposes a two-phase model to find the appropriate supplier combinations, which ensure that customer demand is fulfilled. In Model 1, suppliers are divided

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Notations

h	Hierarchy number, $h = 1, 2, 3, \ldots, H$
i	Part number, $i = 1, 2, 3, \ldots, I$
j	Supplier number, $j = 1, 2, 3, \ldots, J$
k	Supplier cluster number, $k = 1, 2, 3, \ldots, K$
m	Module number, $m = 1, 2, 3, \ldots, M$
s	Quantity discount level
H	Lowest hierarchy number
I	Total number of parts
J	Total number of suppliers
K	Total number of supplier clusters
M	Total number of modules
S	Total number of levels of quantity discount
$b_{i,j}^k$	Part i provided by supplier j belongs to cluster k
$f(OC_{i,j})$	Cost function of the order of supplier j providing part i
$hc_{i,j}$	Unit holding cost of supplier j providing part i
${}^h m$	The mth module in hierarchy h
O_{PC}^k	Production cost centroid in the kth cluster
O_{PQ}^k	Product quality centroid in the kth cluster
O_{PT}^k	Production time centroid in the kth cluster
AD_i	Actual demand for part i
$AT^{h,{}^h m}$	Assembly time for module ${}^h m$
$AC^{h,{}^h m}$	Assembly cost for module ${}^h m$
$C_i^{h,{}^h m}$	Module ${}^h m$ at hierarchy h
D_i	Demand for part i
HC_i	Inventory cost for part i
I_i	Inventory for part i
$MPT^{h,{}^h m}$	Maximum production time of part for module ${}^h m$
$UC_{i,j}$	Unit cost of part i provided by supplier j
$UQ_{i,j}$	Unit quality of part i provided by supplier j
$UT_{i,j}$	Unit time of part i provided by supplier j
$ND_{i,j}^s$	Order quantity level s of part i provided by supplier j
$O_{i,j}$	Order part i provided by supplier j
$OC_{i,j}$	Order cost of part i provided by supplier j
$PT_{i,j}$	Production time of part i provided by supplier j
$PD_{i,j}^s$	Unit price discount at level s of part i provided by supplier j
$ST_{i,j}$	Shipping time of part i provided by supplier j
TC	Total production cost
TQ	Total product quality
TT	Total production time

into several clusters, depending on the characteristics of customers' demands. In Model 2, the more efficient supplier combinations are determined with respect to customer demand in the specific cluster determined by Model 1.

Maria [6] and Kanungo et al. [7] pointed out that, for unsupervised learning, k-means is the fundamental and most widely used clustering algorithm. However, Kanungo et al. [7] stated that selection of the initial cluster centroid for k-means has a great influence on clustering result. If selection of the initial cluster centroid is flawed, the quality of the clustering is compromised. Liu et al. [8] also pointed out that k-means is subject to initial weighting, which yields an unsatisfactory clustering result. A clustering solution that uses k-means is usually confined to a local optimum, during the optimization clustering process. Wang et al. [9] proposed that the probabilistic acceptance of local minima, for SA, could provide strong local search capabilities and avoid confinement to a local optimum. Bandyopadhyay [10] applied SA to clustering and obtained good quality clustering results, as determined through experiments with artificial and real data sets. Wu et al. [11] applied SA to the clustering of incomplete data and the results showed a reduction in clustering errors. Hence, Model 1 uses SA to combine k-means, for supplier clustering.

Supplier evaluation and selection procedures in Model 2 include a quantity discount. Wang et al. [9] stated that when quantity discounts are used in planning, the associated problems are very complex and not easily solved through ordinary commercial software. Tsai [12] pointed out that it is difficult to find a global optimal solution for a nonlinear model with quantity discount variables. As already mentioned, SA provides a strong local search capability, so it is also used to solve for