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Activity-based divergent supply chain planning for competitive advantage in the risky global environment: A DEMATEL-ANP fuzzy goal programming approach

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ABSTRACT

Supply chain management allows modern enterprises to relax their own capacities and produce in a more flexible manner for diversified consumer demands. However, for an enterprise with divergent supply chain (DSC) and multiple product lines, to plan the production allocation for higher competitive advantage in the risky global market is a challenging problem. The existing literature still has not address this problem very well. This paper is aimed to treat this problem by using an integrated approach of activity based costing (ABC) and management, five forces analysis, risk and value-at-risk analysis, decision making trial and evaluation laboratory (DEMATEL), analytic network process (ANP), and fuzzy goal programming (FGP). The proposed model can effectively incorporate the key factors of precise costing, managerial constraints, competitive advantage analysis, and risk management into DSC forecasting and multi-objective production planning. A case study of a consumer-oriented cell phone DSC is also presented. The sensitivity analysis shows that identifying and relaxing crucial constraints can play an important role in DSC planning for higher competitive advantage and lower risk.

1. Introduction

Supply chain (SC) operations enable producers to break through their limits of production with much more flexibility and thus they can focus on consumers' demands. In order to satisfy the diversified demands of consumers, manufacturers might produce various products in which some products may need common components for cost reduction, and form so-called divergent supply chain (DSC); for example, cell phone manufacturers might change the appearances and styles of their cell phones, and maintain the same basic inner-components (Fig. 1).

A SC may be viewed as a DSC if a SC node has one predecessor, but more than one successors (Beamon & Chen, 2001). Mineral industries and consumer-oriented industries often form such type of SC. This type of SC is opposite to a convergent supply chain (CSC). In a DSC, the critical issues of product mix planning, supply chain constraints, forecasting and risk management, and competitive advantage may have relationships with each other. For instance, over production of high risk and low competitiveness products, which may be caused by lack of suitable measurement or not suitably relaxing constraints, could result in ineffectiveness and low capacity efficiency. Especially in today's highly risky global market, how to address these issues and meanwhile achieve high cost-benefit performance has become an important research topic (Syntetos & Boylan, 2006). Fig. 2 shows the external environment and internal constraints for a supply chain (Robbins & Coulter, 2001). We can see that successful supply chain management relies on employing internal resources, finance, and strategy to achieve higher competitive advantage, avoid higher risk, and prepare for potential opportunity.

In the literature of supply chain management, the planning of supply chain is frequently discussed, whereas the integration of precise costing, SC constraints, competitive advantage, and risk management for a DSC still has not been deeply explored. How these elements could be included in DSC planning remains a problem to be solved.

To fill this gap, this research integrates activity based costing (ABC) and management, five forces analysis, risk and value-at-risk analysis, decision making trial and evaluation laboratory (DEMATEL), analytic network process (ANP), and fuzzy goal programming (FGP) for the DSC planning problem. This paper uses cost drivers at various levels (unit, batch, product, facility, supply chain) to measure activity amounts and costs, and identify the constraints of each activity in the supply chain. In measuring respectively the competitive advantage and risk of a product supply chain, DEMATEL is first used to analyze and determine the interdependence relationships between the criteria. Next, ANP evaluates the weights of the alternatives. Value-at-risk (VaR) is also used to measure the potential largest loss. Finally, FGP is used to obtain the optimal product mix and the worst profit. We found that this research

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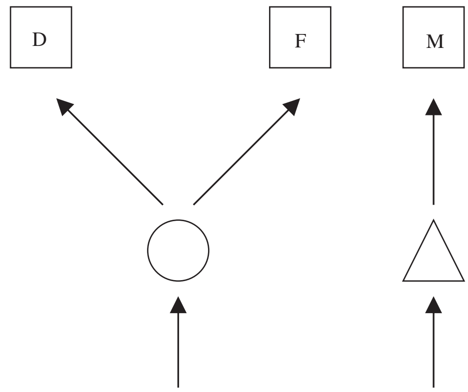

Fig. 1. A divergent supply chain (D, F) and a general supply chain (M).

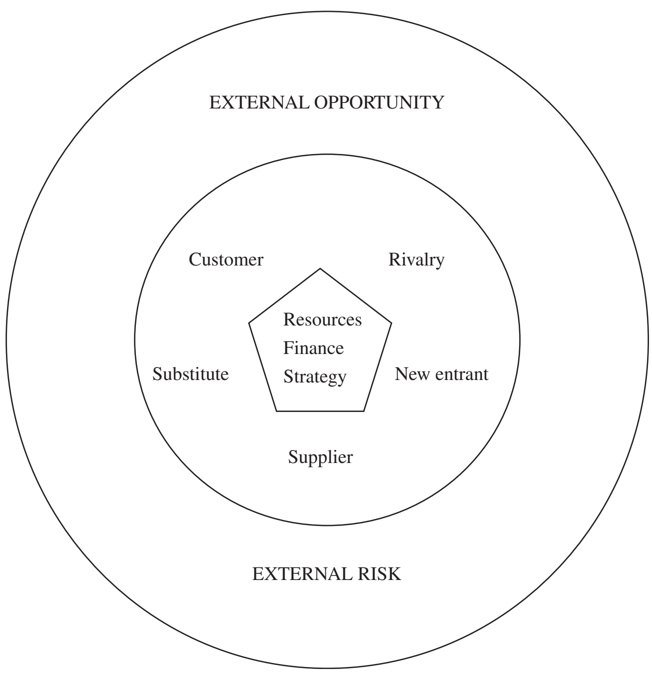

Fig. 2. The external environment and internal constraints for a supply chain.

develops a new approach that can not only improve DSC production planning, but also can efficiently strengthen DSC competitive advantage and risk management.

In the sensitivity analysis of the case study, this paper shows that identifying and relaxing crucial constraints can effectively improve DSC planning for higher competitive advantage and lower risk. In this case, supply chain management time is more crucial than common component capacity constraint. When only the common component constraint is relaxed, the overall planning of product mix is not affected. However, if the supply chain management time is first relaxed, it will increase the production of the higher competitive advantage and lower risk products, meanwhile relaxing common component constraint will also come into effect. Hence, identifying and relaxing crucial constraint is a step with priority in DSC planning. This paper provides a fine application of ABC and DEMATEL-ANP-FGP model in a DSC, and also assists SC managers in making appropriate decisions to decrease the revenue risks of their product mix and raise the overall competitive advantage at the same time.

The rest of this paper is organized as follows: Section 2 presents the literature review. Section 3 discusses the proposed DEMATEL-ANP-FGP model followed by a case study in Section 4. Section 5 concludes this study.

2. Literature review

Multi-product SC planning problems under uncertainty have been discussed by several papers. Mitra, Gudi, Patwardhan, and Sardar (2009) adopted a fuzzy mathematical programming approach to address the multi-site, multi-product, multi-period supply chain planning problem under uncertainty. The slot-based planning model results are obtained for different uncertain scenarios. This model does not require the knowledge of distributions associated with the uncertain parameters. Peidro, Mula, Poler, and Verdegay (2009) proposed a fuzzy mixed-integer linear programming model which considers supply, demand and process uncertainties in supply chain planning. They suggested that the fuzzy formulation is more suitable than deterministic methods in dealing with SC planning which is difficult to obtain precise or certain information, and needed to be modeled by triangular fuzzy numbers. Liang and Cheng (2009) addressed an integrating manufacturing/distribution planning decision (MDPD) problem with multi-product and multi-time period in supply chains by using a fuzzy multi-objective linear programming model (FMOLP) with the consideration of time value of money for each of the operating cost categories in an uncertain environment. Their method aims at minimizing total costs and total delivery time in association with inventory levels, available machine capacity and labor levels at each source, market demand and available warehouse space at each destination, and total budget constraints. Cakır (2009) discussed the problem involving multi-commodity, multi-mode distribution planning by applying the Benders decomposition which is suitable to addressing outsized distribution planning problems characterized with a large commodity set and many transportation mode options. To solve such problems that have an abundant number of discrete variables, the Benders method is efficient enough to isolate a group of decision variables and investigating the problem partially. Vila, Martel, and Beauregard (2006) proposed a mixed integer programming model which maps the industry manufacturing process onto potential production–distribution facility locations and capacity options production–distribution network of divergent process industry companies in a multinational context.

There are also some other papers investigating SC problems under uncertainty. Al-Othman, Lababidi, Alatiqi, and Al-Shayji (2008) adopted a multi-period optimization model to study the effect of uncertainties in market prices and demands on the supply chain of a petroleum organization in an oil producing country. They showed that in the situation with an appropriate balance between crude exports and processing capacities, impacts of economic uncertainties may be tolerated. It is essential that petroleum organization develop resilient production plans for the allocation of the produced crude between direct exports and local processing in an uncertain economic environment. Knemeyer, Zinn, and Eroglu (2009) develops a model that can proactively plan for catastrophic risk events, which specifically builds on existing risk analysis that is often implemented by the insurance industry to quantify the risk of multiple types of catastrophic events on key supply chain locations. The method also provides information to help managers with the generation and selection of appropriate countermeasures and thus mitigate the potential effect of catastrophic events on supply chains. The results reveal that this method is a systematic approach to estimate both the probability of occurrence and the financial impact of potential catastrophic events of those targeted locations with higher risk. Leung, Wu, and Lai (2006) presented a stochastic programming approach to evaluate optimal medium-term production loading plans under an uncertain environment and solve the production planning problem with production plant preference selection constraints. The results show that the model is practical in uncertain economic scenarios. Sodhi and Tang (2009) also developed a stochastic programming formulation for a simple supply chain planning model by extending the linear programming (LP) model of deterministic supply chain planning to take demand uncertainty and cash flows into consideration for the medium term. The model includes the purchase of inputs from a supplier, their conversion to finished goods at a single plant, and the eventual stocking and selling of these goods from a single warehouse facing uncertain demand. The study also examines various modeling and solution choices developed in the asset-liability management (ALM) literature and their applicability to supply chain planning, and results show that simple stochastic programming models will remain as much of an art as it is a science, as they work well when combined with deterministic models in extended ERP/APS systems to provide risk-adjusted plans.

Though the existing papers have rich discussions concerning multi-product planning under uncertainty, they still have not dealt in depth with the DSC control problems about the integration of precise costing, constraints, competitive advantage, and risk management. A better answer could be obtained after the utilization of ABC cost analysis and DEMATEL-ANP-FGP model. This research sets out from this perspective into deeper inquiry.

3. The DEMATEL-ANP fuzzy goal programming model

3.1. Problem formulation

For parsimony, this model simply treats the supply chains of three kinds of products. Two of the products have constraints in common components, and all the three product supply chains are limited by supply chain management time. The product prices have downward risk. Under the various objectives and limits, the decision maker hopes to find the optimal production quantities and its related variables for these products. The major goals are budget, revenue, response time, asset turnover time, risk analysis, and five forces analysis. The main constraints are common component, SC management time, VaR rate, defect rate, late delivery rate, and flexibility rate.

3.2. Activity-based costing, five forces analysis, and other risk management tools

3.2.1. Activity-based costing

Activity-based costing (ABC), which argues that any activity benefiting the production and delivery of goods should be assigned to final cost objects (Johnson & Kaplan, 1987; Kaplan & Cooper, 1998), was proposed in 1980s due to increased overhead (or indirect) cost from automation and technology usage (Lea & Fredendall, 2002). ABC information can be employed to improve operations and eliminate non-value-added costs (Hilton, 2005; Tsai & Hung, 2009a; Tsai & Hung, 2009b). An ABC system has two dimensions, in which the vertical dimension is the cost assignment view, and the horizontal dimension is the performance measurement view. For cost assignment, overhead costs are first assigned to activity cost pools classified by various activity levels such as unit, batch, product, and facility. For instance, unit level activity represents the activity that must be done for each unit of cost object, and batch level activity is for each batch of cost object. After that, activity cost pools are linked to cost objects by cost drivers which mean a characteristic of an activity that causes the incurrence of costs by that activity (Hilton, 2005), and by pool rates which refer to the cost of a cost driver. For example, if machine hour is the cost driver for the cost pool 'machinery', the machinery cost of product A is multiplying the machine hours by the machinery pool rate of product A.

The horizontal dimension is performance measurement. The activity analysis identifies the root causes, activity triggers, and the relationships between the production activities, then the activity performances can be compared with the standard values by benchmarking. In practice, the differences can be represented as 'variance rates' which are the change rates between the standard and actual values.

In the literature of supply chain management, the application of ABC is still discussed very little. In fact, the ABC system can provide a more precise approach for SC costing, constraint and performance measures, which is particularly suitable for DSC planning. Therefore, this paper presents a concise model that incorporates ABC into DSC.

3.2.2. Five forces analysis

Porter (1985) proposed five forces to find the best competitive advantage for companies. The competitive advantage is caused by the five forces variables: new entrants, competitive rivalry, suppliers, consumers, and substitutes (Porter, 1985). The five forces are explained as follows:

(a) The threat of new entrants. The likeliness of new entrants into a production relies on two main factors: the existence of barriers to entry and the expected retaliation. High barriers to entry or strong expected retaliation would decrease the threat of new entrants.
(b) The intensity of competitive rivalry. The intensity of competitive rivalry is affected by many interacting factors: large numbers of competitors or equal competitors, slow rate of industry growth, high fixed cost allocation per value added, lack of brand equity, intermittent industry overcapacity, high diversity of competitors, high exit barriers, and so on.
(c) The bargaining power of suppliers. The raising of prices or lowering of quality of suppliers has a prominent effect on the competitiveness of industries. If an industry cannot adjust its cost structure to lower the rising purchasing costs, their profits may be limited by the actions of their suppliers. Suppliers have a stronger bargaining power when there exists a higher supplier concentration to firm concentration ratio, no satisfactory presence of substitute inputs, low importance of volume to supplier, when the supplier's product is crucial to the consumer's success in the market, cost of inputs are highly relative to selling price of the product, and the ability of forward integration by suppliers is strong.
(d) The bargaining power of consumers. In contrast to an industry's goal to make high cost-profit investment, consumers hope to buy products at the lowest price possible. To lower prices, consumers would bargain in order to buy products with high quality, complete service, and low price. The actions of consumers cause rivalry among enterprises within each industry. The bargaining power of consumers lies in the following factors: high buyer volume, availability of existing substitute products, lack of brand equity within the industry, and allowing buyers the possibility of forward integration.
(e) The threat of substitute products. Substitutes refer to products or services that have the same or similar function, and can bring a similar level of satisfaction to consumers, but have different characteristics. Substitutes put an upward limit to a company's pricing.

Based on the analyses of five forces, this research first used DEMATEL analysis to determine the interdependence relationships between the five forces criteria for the product supply chains, then next used ANP to obtain the comparative advantage weights of the alternatives.

3.2.3. Other risk management tools

Since G30's 1997 derivatives report suggested that corporations with derivative departments should use Value-at-Risk (VaR) as a specific method to evaluate market risk, VaR analysis has been more widely recognized by global management authorities.

VaR is an estimated largest loss in portfolios due to price volatility in a certain period of time and under a certain confidence level. For example, under 95% confidence level within ten days, an estimated VaR of 1 million means that within ten days, there is 5% probability that the value of the portfolio will have a loss of over one million dollars. If variable X_T represents the loss in the future T days and $(1-\alpha)$ is the confidence level, then VaR must satisfy the following condition: $\text{Prob}(X_T \geqslant \text{VaR}) = \alpha$. Because VaR puts emphasis on downward risk, Duarte (1998) proposed a hedging strategy, the optimal VaR hedge, to minimize VaR and lower downward risks.

In consideration of the fact that VaR only provides the information of the largest loss, and cannot deal with individual risks, decision-making risks, and any other risks associated with individual product supply chain, this paper additionally suggests the use of DEMATEL analysis to determine the interdependence relationship between the risk criteria, and then use ANP to evaluate the risk weights of the alternatives. These risk criteria include:

(a) The ability to take risk: To what degree of risk can each individual product supply chain and the whole system take?
(b) Uncertainty: Is there a possibility of reversal? Does the decision maker have enough reliable information about the whole process and consequence of the decision?
(c) Complexity: Are there many incontrollable variables? Are there strong interaction effects between the variables?
(d) Price volatility: Is the standard deviation of the price large in the latest month?
(e) Price vulnerability: Is the current price too high and existing a possibility of price avalanche?

3.3. DEMATEL-ANP and fuzzy goal programming methodology

3.3.1. The DEMATEL method

The DEMATEL method uses digraphs to categorize the influencing factors into two groups: cause group and effect group. There are five steps to perform the DEMATEL process (Tsai, Chou, & Hsu, 2008):

Step 1: Produce the direct-relation matrix. First, set the influence scales: 0 (no influence), 1 (low influence), 2 (medium influence), 3 (high influence), and 4 (very high influence). Next, the pairwise comparisons are made according to influence and direction between criteria. Then, form the direct-relation matrix: a $n \times n$ matrix A, where a_{ij} represents the degree to which the criterion i affects the criterion j.

Step 2: Normalize the direct-relation matrix. Determine the normalized direct-relation matrix $\boldsymbol{X}$ by using the direct-relation matrix $\boldsymbol{H}$:

$$\boldsymbol{X} = k.\boldsymbol{H},$$

$$k = \text{Min}\left(\frac{1}{\max_{1\leqslant i\leqslant n}\sum_{j=1}^{n} a_{ij}},\quad \frac{1}{\max_{1\leqslant j\leqslant n}\sum_{i=1}^{n} a_{ij}}\right),\quad i,j = 1,2,\ldots,n.$$

Step 3: Form the total-relation matrix. The total relation matrix $\boldsymbol{T}$ can be determined by using the normalized direct-relation matrix $\boldsymbol{X}$, where $\boldsymbol{I}$ is the identity matrix

$$\boldsymbol{T} = \boldsymbol{X}(\boldsymbol{I} - \boldsymbol{X})^{-1}.$$

Step 4: Generate a causal diagram. By using expressions below, the sum of rows and the sum of columns are respectively represented as vector D and vector R.

$$T = [s_{ij}]_{n\times n},\quad i,j = 1,2,\ldots,n,$$

$$D = \sum_{j=1}^{n} s_{ij},$$

$$R = \sum_{i=1}^{n} s_{ij}.$$

The "Influence" horizontal axis vector $(D + R)$ shows how much importance the criterion has, and the "Relation" vertical axis $(D - R)$ categorizes criteria into a cause group and an effect group. When $(D - R)$ is positive, the criterion will be assigned to the cause group, and when negative, the effect group. Thus, by mapping the dataset of the $(D + R, D - R)$, we can get the causal diagram.

Step 5: Set threshold value and draw the impact-digraph-map. Decision makers and/or experts should set a threshold value for the influence level to make sure an appropriate impact-digraph-map is acquired. Only those elements with an influence level higher than the threshold value in matrix $\boldsymbol{T}$ are selected and included in the impact-digraph-map.

3.3.2. The ANP method

After identifying the interdependence relationships between the criteria by the DEMATEL process, the ANP process will be used to evaluate the weights of the alternatives. The ANP method includes two major phases: the first phase performs pairwise comparisons for each of the dependency relationships to generate the relative importance weights, and the second phase, the supermatrix calculation, is split into three minor parts in the procedure: the formation of the supermatrix, the normalization of the supermatrix, and the convergence to the solution. The converged supermatrix can reveal the information of the relative priorities for each of the alternatives (Tsai & Chou., 2009; Saaty, 1996).

Step 1: Pairwise comparisons. The pairwise comparisons of the elements within each cluster are conducted to form pairwise comparison matrices. The valuation scales, recommended by Saaty, are ranked 1 as equal importance, 3 as moderate importance, 5 as strong importance, 7 as very strong or demonstrated importance, and 9 is extreme importance. Even numbered values are placed between the above importance levels. Reciprocal values (e.g. 1/5, 1/7) refers to less importance, strongly less importance, ... and so on. After finishing pairwise comparisons, the relative importance weight for each component is calculated by using MATLAB software, and with A as the pairwise comparison matrix, the weights are evaluated through expression $Aw = \lambda_{max}w$. λ_{max} means the largest eigenvalue of A here. w refers to the eigenvectors for the principal eigenvalue λ_{max}, which is also the priority vector of the elements. For data consistency, a consistency index (CI) and consistency ratio (CR) must be examined: CI $=(\lambda_{max} - n)/(n - 1)$, where n refers to the number of components listed in the pairwise comparison matrix; and the CR is the value dividing the CI by a random inconsistency (RI) value. The RI value can be found in most AHP and ANP reference books. The pairwise comparison matrix will be consistent when CR < 0.10. The comparison weights can also be obtained by an AHP/ANP software such as *Expert Choice*.

Step 2: The formation and normalization of the supermatrix. The supermatrix is formed by using the priority vectors of each pairwise comparison matrices. Saaty recommends that the sums of the columns should be normalized to equal a value of 1, i.e. column stochastic. In this paper, all clusters are of equal importance.

Step 3: The convergence to a solution. The last part is to give a priority ranking to each of the alternatives. Saaty suggests to raise the supermatrix $\mathbf{M_s}$ to the largest power when the convergence occurs and thus find a solution.

3.3.3. The fuzzy goal programming methodology

In the problem of DSC production planning, the goals of the decision makers may be fuzzy for the consideration of flexibility and vagueness in the preferences. We adopted a FGP approach to describe such DSC decision framework (Biswas & Pal, 2005). The advantage of FGP is that this tool can handle priority structure of objectives with fuzzy goals.

If the goal has a lower limit $(V_g - \varepsilon_g)$, then the membership function $\mu_g(\mathbf{x})$ in different intervals is Eq. (1).

$$\mu_g(\mathbf{x}) = \begin{cases} 1 & \text{if } f_g(x) \geqslant V_g, \\ [f_g(\mathbf{x}) - (V_g - \varepsilon_g)]/\varepsilon_g & \text{if } V_g - \varepsilon_g \leqslant f_g(\mathbf{x}) < V_g, \\ 0 & \text{if } f_g(\mathbf{x}) < V_g - \varepsilon_g, \end{cases} \tag{1}$$

where $\mathbf{x}$ is the vector of decision variables.

On the contrary, if the goal has an upper limit $(V_g + \varepsilon_g)$, then the membership function $\mu_g(\mathbf{x})$ in different intervals is Eq. (2)

$$\mu_g(\mathbf{x}) = \begin{cases} 1 & \text{if } f_g(x) \leqslant V_g, \\ [(V_g + \varepsilon_g) - f_g(x)]/\varepsilon_g & \text{if } V_g < f_g(x) \leqslant V_g + \varepsilon_g, \\ 0 & \text{if } f_g(x) > V_g + \varepsilon_g, \end{cases} \tag{2}$$

The FGP model of the specified problem can be stated as follows.

3.4. The model

Minimize

$$P_1(d_1^- + d_2^-) + P_2(d_3^- + d_4^-) + P_3(d_5^- + d_6^-). \tag{3}$$

In this model, minimizations of under achievements (d_g^-, $g = 1, 2, \ldots, 6$) of the targeted goals are the objectives that have several priorities (P_1, P_2, P_3). The higher priority objectives, such as P_1, must be first satisfied and then the lower priority objectives. The priority and the weight of d_g^- are judged by the decision maker.

Subject to

[Activity-based costs (including logistics and quality costs)]

$$\left[(V_1 + \varepsilon_1) - \left(\sum_{i=1}^{3}\sum_{m=1}^{M} c_m \beta_{im} x_i + \sum_{i=1}^{3}\sum_{j \in UN,F} w_j \gamma_{ij} x_i + \sum_{i=1}^{3}\sum_{j \in BT,S} w_j \delta_{ij} B_{ij} + \sum_{i=1}^{3}\sum_{j \in PR} w_j \zeta_{ij} \phi_i\right)\right] \Big/ \varepsilon_1 + d_1^- - d_1^+ = 1. \tag{4}$$

Eq. (4) controls the upper tolerance limit of budget. Each unit of product i needs β_{im} quantity of component m. c_m is component m's unit cost. For the unit-level activities (UN), product i needs γ_{ij} quantity of cost driver (or activity) j. w_j is the driver pool rate for activity j. Similarly, product i respectively needs δ_{ij} and ζ_{ij} quantity of cost driver for batch-level activities (BT) and product-level activities (PR). B_{ij} is the batch quantity for product i and batch-level activity j. ϕ_i is a 0/1 variable that equals 1 if product i is produced and 0 otherwise. Facility-level activities (F) can be treated as unit-level activities, and supply chain-level activities (S) can be treated as batch-level activities, because their cost drivers are in the form of unit and batch respectively. $V_1 + \varepsilon_1$ is the upper tolerance limit of budget.

[Revenue]

$$\left[\sum_{i=1}^{3} p_i x_i - (V_2 - \varepsilon_2)\right] \Big/ \varepsilon_2 + d_2^- - d_2^+ = 1. \tag{5}$$

Eq. (5) controls the lower tolerance limit of revenue $(V_2 - \varepsilon_2)$. p_i denotes the price for product i.

[Variance rate of response time]

$$\left[\sum_{i=1}^{3}\sum_{e \in UN} f_{ie} x_i + \sum_{i=1}^{3}\sum_{e \in BT} z_{ie} B_{ie} - (V_3 - \varepsilon_3)\right] \Big/ \varepsilon_3 + d_3^- - d_3^+ = 1. \tag{6}$$

Eq. (6) controls the lower tolerance limit of response time performance $(V_3 - \varepsilon_3)$. f_{ie} is the variance rate of response time of e unit-level activities for product i. Similarly, z_{ie} is the variance rate of response time of e batch-level activities for product i. The definition of variance rate has been stated in Section 3.2.1.

[Variance rate of asset turnover time]

$$\left[\sum_{i=1}^{3} t_i x_i - (V_4 - \varepsilon_4)\right] \Big/ \varepsilon_4 + d_4^- - d_4^+ = 1. \tag{7}$$

Eq. (7) controls the lower tolerance limit of asset turnover time performance $(V_4 - \varepsilon_4)$. t_i is the variance rate of asset turnover time for product i. The definition of variance rate has been stated in Section 3.2.

[Risk analysis]

$$\sum_{i=1}^{3} \sigma_i x_i + d_5^- - d_5^+ = MINR. \tag{8}$$

Eq. (8) set the minimum risk goal ($MINR$). σ_i is the risk weight for product i after expert assessment.

[Five forces analysis]

$$\sum_{i=1}^{3} \rho_i x_i + d_6^- - d_6^+ = MAXF. \tag{9}$$

Eq. (9) set the maximum comparative advantage goal ($MAXF$). ρ_i is the five forces weight for product i after DEMATEL-ANP process.

[Common component quantity constraint]:

$$\sum_{i=1}^{2} \beta_{ia} x_i \leqslant MAXQ. \tag{10}$$

Eq. (10) is the common component quantity constraint ($MAXQ$). β_{ia} is the usage of 'a' common component for one unit of product i.

[Supply chain management time]

$$\sum_{i=1}^{3}\sum_{b \in S} \delta_{ib} B_{ib} \leqslant MAXS. \tag{11}$$

Eq. (11) is the supply chain management time constraint ($MAXS$). δ_{ib} is the usage of supply chain management time for one batch of product i.

[VaR rate constraint]

Table 1
The DEMATEL initial direct-relation matrix.

	Customer	Supplier	New entrant	Substitute	Rivalry
Customer	0.000	3.000	3.333	3.333	3.667
Supplier	1.333	0.000	1.333	2.000	3.333
New entrant	3.333	2.000	0.000	3.000	2.333
Substitute	3.000	2.000	3.667	0.000	2.333
Rivalry	4.000	2.667	2.667	3.333	0.000

Table 2
The DEMATEL normalized direct-relation matrix.

	Customer	Supplier	New entrant	Substitute	Rivalry
Customer	0.000	0.225	0.250	0.250	0.275
Supplier	0.100	0.000	0.100	0.150	0.250
New entrant	0.250	0.150	0.000	0.225	0.175
Substitute	0.225	0.150	0.275	0.000	0.175
Rivalry	0.300	0.200	0.200	0.250	0.000

Table 3
The DEMATEL total-relation matrix.

	Customer	Supplier	New entrant	Substitute	Rivalry	D
Customer	1.120	1.127	1.267[a]	1.313[a]	1.316[a]	6.144
Supplier	0.827	0.617	0.788	0.856	0.919	4.007
New entrant	1.142	0.925	0.901	1.121	1.074	5.163
Substitute	1.145	0.940	1.136	0.956	1.091	5.268
Rivalry	1.316[a]	1.081	1.202[a]	1.278[a]	1.066	5.944
R	5.551	4.690	5.294	5.524	5.467	
D + R	11.695	8.697	10.457	10.793	11.411	
D − R	0.593	−0.683	−0.132	−0.256	0.477	

[a] The value is higher than the threshold value 1.200, which means that the column factor strongly affects the row factor.

$$\sum_{i=1}^{3} v_i p_i x_i \leqslant v \sum_{i=1}^{3} p_i x_i. \tag{12}$$

Eq. (12) limits the maximum VaR value. v_i is the VaR rate for one dollar of product i revenue. v is the maximum VaR rate.

[Defect rate]

$$\sum_{i=1}^{3} \theta_i x_i \leqslant \theta \sum_{i=1}^{3} x_i. \tag{13}$$

Eq. (13) limits the maximum defect rate. θ_i is the defect rate for product i. θ is the maximum defect rate.

[Late delivery rate]

$$\sum_{i=1}^{3} \lambda_i x_i \leqslant \lambda \sum_{i=1}^{3} x_i. \tag{14}$$

Eq. (14) limits the maximum late delivery rate. λ_i is the late delivery rate for product i. λ is the maximum late delivery rate.

[Flexibility rate]

$$\sum_{i=1}^{3} \eta_i x_i \geqslant \eta \sum_{i=1}^{3} x_i. \tag{15}$$

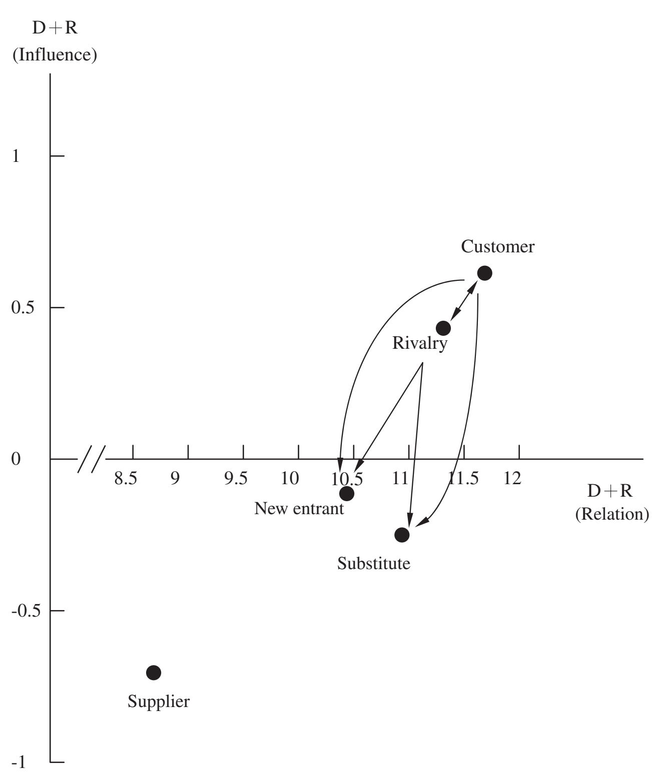

Fig. 3. The impact-digraph-map of DEMATEL total relation.

Eq. (15) limits the minimum flexibility rate. η_i is the flexibility rate for product i. η is the minimum flexibility rate

$$x_i \leqslant h_{ij} B_{ij} \leqslant x_i + (h_{ij} - 1), \quad q_i \phi_i \leqslant x_i \leqslant Q_i \phi_i,$$
$$0 \leqslant \phi_i \leqslant 1, \quad \forall i, \ i = 1, 2, 3. \tag{16}$$

In Eq. (16), h_{ij} is the batch size of one batch for j activity on product i. q and Q are respectively minimum and maximum capacities for product i

$$d_g^-, d_g^+ \geqslant 0 \quad \forall g, \ g = 1, 2, \ldots, 6,$$

$$\{x_i, B_{ij}, \phi_i, h\} \in \text{positive integer}.$$

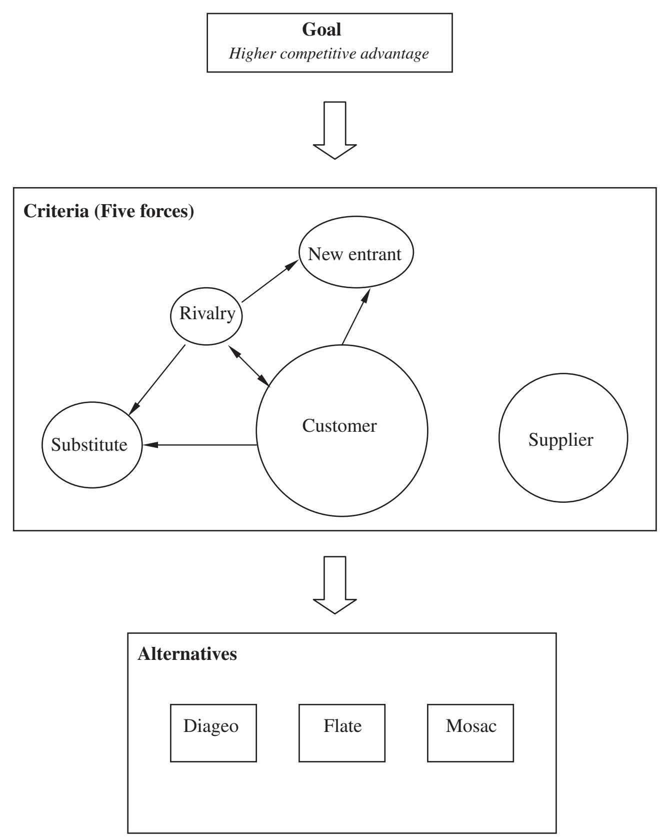

Fig. 4. The ANP relationships for the three product supply chains.

Table 4
The pairwise comparison matrix with respect to customer force.

Customer	New entrant	Substitute	Rivalry	Weight
New entrant	1.000	0.500	0.333	0.163
Substitute	2.000	1.000	0.500	0.297
Rivalry	3.000	2.000	1.000	0.540

4. Case study and discussion

Headquartered in east China, Company Z is a leading provider of designing and manufacturing high-end mobile communication devices for distributors in over 42 countries. The company also has branch corporations in USA, UK, EU, Japan, and the emerging markets including Russia, India, and Brazil. In order to lower cost, Company Z builds manufacturing supply chains in mid-west China, capable of producing over 2,000,000 cell phones every quarter. Because the production of key components substantially relies on Taiwan's suppliers, Company Z is often confronted by SC production planning problems. The decision maker desires to know what are the critical production constraints, the effects of relaxing the constraints, and how to decide the production allocation for its diversified product supply chains with possible revenue risks.

Based on the situation and decision model stated in Chapter 3, Company Z is considering three cell phone products: Diageo, Flate, and Mosac. Diageo and Flate have a common component. The first step is to determine the DEMATEL-ANP weights of five forces and risks for the three products. The second step is to substitute the relevant data to the FGP model. At last, the final step is to perform the sensitivity analysis.

4.1. The determination of the DEMATEL-ANP weights

As for the five forces analysis, the DEMATEL initial direct-relation matrix which describes the influences of the column elements on the row elements is shown in Table 1. Table 2 shows the DEMATEL normalized direct-relation matrix. Table 3 is the DEMATEL total-relation matrix. If the value is higher than the threshold value 1.200, then the column factor is deemed strongly affecting the row factor. Based on Table 3, Fig. 3 shows the impact-digraph-map of DEMATEL total relation. We can see that 'Supplier' is an independent criterion, while 'New entrant' and 'Substitute' are pure influenced criteria, and 'Rivalry' and 'Customer' have influences on each other and 'New entrant' and 'Substitute'.

Based on the DEMATEL analysis, Fig. 4 shows the ANP relationships for the three product supply chains. The goal is to achieve higher competitive advantage by using the five forces criteria. Table 4 shows the pairwise comparison matrix with respect to customer force. For instance, the decision-makers or experts will be asked to determine the relative importance of 'New entrant' to 'Substitute' with respect to customer force. The weights of 'New entrant', 'Substitute', and 'Rivalry' are (0.163, 0.297, 0.540), respectively (see the bold value in Table 5).

Table 5
The ANP initial supermatrix (**M**) for competitive advantage (CPAG) alternatives.

	Goal	Five forces					Alternatives		
	CPAG	Customer	Supplier	New entrant	Substitute	Rivalry	Diageo	Flate	Mosac
CPAG	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Customer	0.432	0.000	0.000	0.000	0.000	0.581	0.000	0.000	0.000
Supplier	0.241	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
New entrant	0.117	**0.163**	0.000	0.000	0.000	0.154	0.000	0.000	0.000
Substitute	0.121	**0.297**	0.000	0.000	0.000	0.265	0.000	0.000	0.000
Rivalry	0.089	**0.540**	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Diageo	0.000	0.243	0.343	0.218	0.367	0.243	1.000	0.000	0.000
Flate	0.000	0.525	0.326	0.460	0.431	0.525	0.000	1.000	0.000
Mosac	0.000	0.232	0.331	0.322	0.202	0.232	0.000	0.000	1.000

Table 6
The ANP normalized supermatrix ($\mathbf{M_s}$) for competitive advantage (CPAG) alternatives.

	Goal	Five forces					Alternatives		
	CPAG	Customer	Supplier	New entrant	Substitute	Rivalry	Diageo	Flate	Mosac
CPAG	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Customer	0.432	0.000	0.000	0.000	0.000	0.291	0.000	0.000	0.000
Supplier	0.241	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
New entrant	0.117	0.082	0.000	0.000	0.000	0.077	0.000	0.000	0.000
Substitute	0.121	0.148	0.000	0.000	0.000	0.133	0.000	0.000	0.000
Rivalry	0.089	0.270	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Diageo	0.000	0.122	0.343	0.218	0.367	0.122	1.000	0.000	0.000
Flate	0.000	0.263	0.326	0.460	0.431	0.263	0.000	1.000	0.000
Mosac	0.000	0.116	0.331	0.322	0.202	0.116	0.000	0.000	1.000

Table 7
The ANP limited supermatrix ($\mathbf{M_s^9}$) for competitive advantage (CPAG) alternatives.

	Goal	Five forces					Alternatives		
	CPAG	Customer	Supplier	New entrant	Substitute	Rivalry	Diageo	Flate	Mosac
CPAG	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Customer	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Supplier	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
New entrant	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Substitute	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Rivalry	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Diageo	**0.291**	0.266	0.343	0.218	0.367	0.265	1.000	0.000	0.000
Flate	**0.445**	0.500	0.326	0.460	0.431	0.501	0.000	1.000	0.000
Mosac	**0.265**	0.236	0.331	0.322	0.202	0.236	0.000	0.000	1.000

Table 8
Basic data of the FGP model.

Product supply chain		Diageo	Flate	Mosac	*Limits, ranges*
Cost					181000000; 2000000
Direct material cost ($) (per unit)	$c\beta$	42	49.5	42.3	
Unit-level cost ($) (per unit)	$w\gamma$	37.3	43.2	44.5	
Batch-level cost ($) (average per batch)	$w\delta$				
Pool rate ($) (per hour)	w	145	137.4	142.6	
Hours per batch	δ	5	6	5	
Average batch size	h	20	20	20	
Product-level cost ($) (per product type)	$w\zeta$	38900	43500	50000	
Facility-level[a] cost ($)(per unit)	$w\gamma$	11.5	12	10.3	
Supply chain-level[b] cost ($):	$w\delta$				
Management hours per batch	δ_{ib}	30	26	44	4300
Pool rate ($) (per hour)	w	80	75	82	
Batch size (thousand units)	h	10	10	10	
Revenue					290000000; 2000000
Existing price ($)	p	210	225	235	
Common component usage (per unit)	β_{ia}	1	1	0	920000
Response time					90000; 2000
Variance rate of unit response (h)	f	0.15	−0.12	0.21	
Variance rate of batch response (h)	z	−0.06	0.15	0.13	
Variance rate of asset turnover time (h)	t	0.14	0.23	0.31	293000; 2000
Risk analysis weight	σ	0.351	0.327	0.322	500000
Five forces analysis weight	ρ	0.291	0.445	0.265	500000
VaR rate	v	0.15	0.21	0.30	0.25
Defect rate	θ	0.07	0.06	0.05	0.07
Late delivery rate	λ	0.05	0.05	0.06	0.06
Flexibility rate	η	0.14	0.15	0.2	0.14
Maximum production (thousand units)	Q	500	500	500	
Minimum production (thousand units)	q	10	10	10	

[a] Cost driver is direct labor hour and similar to unit level.
[b] Cost driver is order batch.

Table 9
The FGP model of divergent supply chain planning.

Minimize	
$P_1(d_1^- + d_2^-) + P_2(d_3^- + d_4^-) + P_3(d_5^- + d_6^-)$	Objective function
Subject to	
$\{181000000 - [(42 * x_1 + 49.5 * x_2 + 42.3 * x_3) + (37.3 * x_1 + 43.2 * x_2 + 44.5 * x_3) +$ $(145 * 5 * B_{1A} + 137.4 * 6 * B_{2A} + 142.6 * 5 * B_{3A}) + (38900 * F_1 + 43500 * F_2 + 50000 * F_3) +$ $(11.5 * x_1 + 12 * x_2 + 10.3 * x_3) + (30 * 80 * B_{1S} + 26 * 75 * B_{2S} + 44 * 82 * B_{3S})]/2000000 + d_1^- - d_1^+ = 1$	ABC
$[(210 * x_1 + 225 * x_2 + 235 * x_3) - 290000000]/2000000 + d_2^- - d_2^+ = 1$	Revenue
$[(0.15 * x_1 - 0.12 * x_2 + 0.21 * x_3 - 0.06 * B_{1A} + 0.15 * B_{2A} + 0.13 * B_{3A}) - 90000]/2000 + d_3^- - d_3^+ = 1$	Response time
$[(0.14 * x_1 + 0.23 * x_2 + 0.31 * x_3) - 293000]/2000 + d_4^- - d_4^+ = 1$	Asset turnover time
$(0.351 * x_1 + 0.327 * x_2 + 0.322 * x_3) + d_5^- - d_5^+ = 500000$	Risk analysis
$(0.291 * x_1 + 0.445 * x_2 + 0.265 * x_3) + d_6^- - d_6^+ = 500000$	Five forces analysis
$x_1 + x_2 \leqslant 920000$	Common component
$30 * B_{1S} + 26 * B_{2S} + 44 * B_{3S} \leqslant 4300$	SC management time
$0.15 * 210 * x_1 + 0.21 * 225 * x_2 + 0.30 * 235 * x_3 \leqslant 0.25 * (210 * x + 1 + 225 * x_2 + 235 * x_3)$	VaR rate
$0.07 * x_1 + 0.06 * x_2 + 0.05 * x_3 \leqslant 0.07 * (x_1 + x_2 + x_3)$	Defect rate
$0.05 * x_1 + 0.05 * x_2 + 0.06 * x_3 \leqslant 0.06 * (x_1 + x_2 + x_3)$	Late delivery rate
$0.14 * x_1 + 0.15 * x_2 + 0.2 * x_3 \geqslant 0.14 * (x_1 + x_2 + x_3)$	Flexibility rate
$x_1 \leqslant 20 * B_{1A} \leqslant x_1 + 19; x_2 \leqslant 20 * B_{2A} \leqslant x_2 + 19; x_3 \leqslant 20 * B_{3A} \leqslant x_3 + 19;\ x_1 \leqslant 10000 * B_{1S} \leqslant x_1 + 9999;$ $x_2 \leqslant 10000 * B_{2S} \leqslant x_2 + 9999; x_3 \leqslant 10000 * B_{3S} x_3 + 9999$	Batch size
$10000 * F_1 \leqslant x_1 \leqslant 500000 * F_1; 10000 * F_2 \leqslant x_2 \leqslant 500000 * F_2; 10000 * F_3 \leqslant x_3 \leqslant 500000 * F_3$	Capacity
$\{x_1, x_2, x_3, B_{1A}, B_{2A}, B_{3A}, B_{1S}, B_{2S}, B_{3S} \in$ Positive integer	
$\{F_1, F_2, F_3 \in \{0, 1\}$	
$d_g^-, d_g^+ \geqslant 0$ for $g = 1, 2, \ldots, 7$	

The ANP initial supermatrix (**M**) and its general submatrices for competitive advantage (CPAG) alternatives are shown in Table 5. All the weights satisfy the consistency condition. Table 6 shows the ANP normalized supermatrix ($\mathbf{M_s}$). After raising the power to 9, the normalized supermatrix converges (Table 7). We can see that Flate has the highest weight (0.445) in competitive advantage, and then Diageo (0.291), and Mosac (0.265) (see the bold value in Table 7).

The process of the risk DEMATEL-ANP analysis is similar. Due to space limitation, the risk analysis by using the criteria of 'the ability to take risk', 'uncertainty', 'complexity', 'price volatility', and 'price vulnerability' is not shown. After the risk DEMATEL-ANP analysis, the product with the least risk is Diageo (0.351), and then Flate (0.327), and Mosac (0.322).

4.2. The results of the FGP model

The basic data of the FGP model are listed in Table 8. The cost driver of facility-level cost is direct labor hour and similar to unit level, and the cost driver of supply chain-level cost is order batch.

Table 10
Results of the FGP model of divergent supply chain planning.

Product supply chain	Total	Diageo	Flate	Mosac
Production quantity(x_i) (units)	1,310,000	420,000	490,000	400,000
Average batches (B_{iA})		21,000	24,500	20,000
SC management batches (B_{iS})		42	49	40
Product index (F_i)		1	1	1
Cost ($)	178,434,870	5,350,0700	7,163,9850	5,329,4320
Revenue ($)	292,450,000	88,200,000	110,250,000	94,000,000
Profit ($)	114,015,130	34,699,300	38,610,150	40,705,680
Gross profit rate	0.390	0.393	0.350	0.433
VaR ($)	64,582,500	13,230,000	23,152,500	28,200,000
The worst revenue ($)	227,867,500	74,970,000	87,097,500	65,800,000
The worst profit ($)	49,432,630	21,469,300	15,457,650	12,505,680
The worst gross profit rate	0.217	0.286	0.177	0.190
Common component usage (units)	910,000	420,000	490,000	0
SC management time (h)	4294	1260	1274	1760

Table 11
Sensitivity analysis of the FGP model.

Product supply chain	Total	Diageo	Flate	Mosac
Scenario I[a]				
Production quantity	1,310,000	420,000	490,000	400,000
Profit	114,015,130	34,699,300	38,610,150	40,705,680
Gross profit rate	0.390	0.393	0.350	0.433
VaR	64,582,500	13,230,000	23,152,500	28,200,000
The worst profit	49,432,630	21,469,300	15,457,650	12,505,680
The worst gross profit rate	0.217	0.286	0.177	0.190
Scenario II[b]				
Production quantity	1,310,000	420,000	490,000	400,000
Profit	114,015,130	34,699,300	38,610,150	40,705,680
Gross profit rate	0.390	0.393	0.350	0.433
VaR	64,582,500	13,230,000	23,152,500	28,200,000
The worst profit	49,432,630	21,469,300	15,457,650	12,505,680
The worst gross profit rate	0.217	0.286	0.177	0.190
Scenario III[c]				
Production quantity	1,313,901	**424,740**	**495,258**	393,903
Profit	**114,195,658.9**	35,090,083	39,023,920.2	40,081,655.7
Gross profit rate	0.390	0.393	0.350	0.433
VaR	64,550,412	13,379,310	23,400,940.5	27,770,161.5
The worst profit	**49,645,246.9**	21,710,773	15,622,979.7	12,311,494.2
The worst gross profit rate	0.217	0.286	0.177	0.190
Scenario IV[d]				
Production quantity	1,314,114	**428,238**	**494,660**	391,216
Profit	**114,164,255.8**	35,380,169.6	38,976,712.8	39,807,373.4
Gross profit rate	0.390	0.393	0.350	0.433
VaR	64,442,910	13,489,497	23,372,685	27,580,728
The worst profit	**49,721,345.8**	21,890,672.6	15,604,027.8	12,226,645.4
The worst gross profit rate	0.217	0.286	0.177	0.190

[a] Original case.
[b] Only relaxing the common component usage ($MAXQ$ = 923,000).
[c] Only relaxing the supply chain management time ($MAXS$ = 4350).
[d] Both relaxing the supply chain management time ($MAXS$ = 923,000) and the common component usage ($MAXQ$ = 4350).

The calculation of activity costs is the same as Section 3.2.1. The variance rate means the change rate of actual value relative to standard value, so variance rate 0.15 means that the actual value is 15% larger than the standard value. As for the weights of risk analysis, larger value refers to less risk. The VaR rate refers to the largest loss rate deviating from existing price.

The data in Table 8 are substituted in our FGP model, which is shown in Table 9. The abbreviation B_{iA} means average batch size, B_{iS} means SC order batch size, and F_i means ϕ_i in the equation model.

Table 10 shows the results of the FGP model. Due to the production constraints, all the three products can not produce to the largest capacities. Flate is produced most, and then Diageo, and Mosac is the least. We can see that Diageo has the most risk adjusted profit (i.e. the worst profit), which is relative to Mosac that has the most profit. This model can effectively avoid producing too much Mosac that has the highest risk and lowest competitive advantage.

4.3. The sensitivity analysis

Table 11 shows the sensitivity analysis of the FGP model, which has four scenarios: the original case, only relaxing the common component usage ($MAXQ$ = 923,000), only relaxing the supply chain management time ($MAXS$ = 4350), and both relaxing the supply chain management time ($MAXS$ = 923,000) and the common component usage ($MAXQ$ = 4350). The constraint of supply chain management time is more important than the common component capacity constraint, because only when the supply chain management time is first relaxed will the relaxing of common component constraint generate effect, and raise the production levels of the products of higher competitive advantage and lower risk (see the bold value in Table 11). The sensitivity analysis implies that identifying and relaxing supply chain management time plays a critical role in DSC planning.

5. Conclusion

In the increasingly risky global market, the integration of precise costing, constraint control, competitive advantage and risk management is a critical problem for a divergent supply chain (DSC). However, existing papers have not yet proposed a very suitable planning approach for this problem. This paper suggests that this problem can be solved by applying an ABC system and a DEMATEL-ANP-FGP model.

On the resource side, this research utilized the cost drivers at each level (unit, batch, product, facility, supply chain) to measure the activity amounts and costs, and built the constraints of total budget goals, gross revenue goals, the performance of response time and asset turnover time, SC management time, defect rate, late delivery rate, flexibility rate, and capacity. For measuring the competitive advantage and risk of the product supply chains, DEMATEL is first used to determine the interdependence relationships between each criterion, and then ANP determines the weights of the alternatives, and value-at-risk determines the largest losses. Finally, the FGP model of multi-objective decision making finds the optimal product mix, and the worst profit.

In the sensitivity analysis of our case study, the constraint of supply chain management time is even more crucial than the common component capacity constraint, because only when the supply chain management time is first relaxed will the relaxing of common component constraint come into effect, and increase the production levels of the products of higher competitive advantage and lower risk; thus in this case, identifying and relaxing supply chain management time plays a critical role in DSC planning.

In practice, this paper suggests that in the highly risky global market, the cost drivers and cost information of ABC can be used in DSC planning to identify the costs and constraints of the supply chain. Then by combining the evaluations of competitive advantage and risk with a DEMATEL-ANP-FGP model, a company can meet its budget and revenue goals, and achieve optimal planning for higher competitive advantage and lower risk.

The contribution of this research is developing a sound model of ABC and DEMATEL-ANP-FGP for DSC forecasting and planning. In practice, the proposed model can help DSC managers in making better decisions for lower revenue risk and higher competitive advantage.

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