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Full Length Research Paper

A (data envelopment analysis) DEA-based systematic approach for selection of strategic alliance candidates: Case by the biotechnology industry

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Enterprises become more and more difficult to maintain success in the highly competitive environment. This is the reason why many enterprises start searching for strategic alliance partners to strengthen their competitive advantage. However, facing a future of uncertainty, choosing the suitable partner of strategic alliance has become a difficult task. Based on data envelopment analysis and heuristic techniques, this study proposes a new systematic approach, which calls alliance candidate selection. The objective of alliance candidate selection is to assist biotech companies to evaluate the operation efficiency and find the best candidate of strategic alliance. Realistic data are collected from biotechnology businesses of Taiwan published stock market. Target company and 19 biotechnology companies for decision making units were collected. This research tries to help target company to find the right alliance partners for future integration. By analysis of alliance candidate selection, the results show that, the predicted benefits of 3 candidates as first priority 4 ones suggested and 10 of the ones not recommended. The results are sound for enterprises to find the future candidates of strategic alliance by many industry peoples. Alliance candidate selection can effectively provide all the essential analysis and recommendations to enterprises, for finding the right candidate of strategic alliance.

Key words: Strategic alliance, data envelopment analysis, biotechnology, efficiency.

INTRODUCTION

The technology policy of many countries chooses biotechnology for full support and development. Biotechnology industry becomes one of the most past booming industries in the world. No doubt, this is a new industry and people still try to find a way up. Nevertheless, with rapid growth of the global competition, enterprises strongly feel that their advantage is not easy to continue longer in the market, especial the competence strategy of this new industry. This is the reason why many enterprises start searching for strategic alliance partners in order to strengthen their competitive advantage for the ultimate success in the market. However, facing a future of uncertainty, choosing the suitable partner of "strategic alliance" has become a difficult task. The objective of this paper is to develop an effective method to assist biotech companies to evaluate the operation efficiency and find the best candidate of strategic alliance. Based on the methodology of data envelopment analysis (DEA) and heuristic techniques, this research develops an evaluation method which calls alliance candidate selection (ACS). ACS will be a very effective tool by using evaluation models to provide top managers with an effective method to find the best partner of strategic alliance under some certain control factors; because the merge and alliance has been a very common strategy for business to have more choices and fast expansion. Besides, mutual learning is another advantage.

Most of DEA applications focused on performance evaluation, some are in the area of mergers and acquisitions (Sufian and Habibullah, 2009). The research of Bhattacharyya et al. (1997) shows that, government owned banks possess more operational efficiency than privately owned banks, but less efficiency than foreign

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banks. Camanho and Dyson (2005) enhance cost efficiency measurement methods. The results obtained in the case study show that, the DEA models can provide robust estimates of cost efficiency even in situations of price uncertainty. Lee et al. (2005) discuss a description of a DEA model for analysis of the control performance for a specific context for electronic data interchange (EDI) in the context of finance and trade. Homburg (2001) investigates the use of DEA for activity-based management and pros and cons of DEA as applied to benchmark activities. Mota et al. (1999) provide a quantitative model for activity-based management (ABM). A real case study of a drill factory is used to illustrate the application of the model. Co and Chew (1997) use DEA to analyze the performance and R&D expenditures in American and Japanese manufacturing firms. An approach based on DEA is proposed by Chang and Lo (2005) for measuring the relative efficiency of an ISO 9000 certified firm's ability to achieve organizational benefits. Luo and Donthu (2005) use DEA and Stochastic Frontier (SF) to show that, top 100 marketers' advertising spending in print, broadcast, and outdoor media are not efficient and could bring in 20% more sales. Cook and Zhu (2003) use DEA for productivity measurement of highway maintenance crews as maximum achievable by reduction in resources without impacting the outputs from the process. Durand and Vargas (2003) analyze the ownership, organization, and private firms' efficient by DEA. Forker et al. (1997) combine nonlinear DEA and linear regression analyses, and then demonstrate that Total Quality Management (TQM) practices are related to performance. However, DEA cannot only be used in performance evaluation and can be extended more.

Some researches extend DMU combination in DEA to study strategy. Some other researcher such as Shaffer (1993) suggests that, mergers have the potential to produce efficiencies. Worthington (2004) uses DEA and the multinomial logic model to evaluate the determinants of merger and acquisition (M&A) activity in Australian credit unions. The results indicate that, asset size and quality, management ability, earnings and liquidity impose significant influences on the level of M&A. Lubatkin and Srinivasan (1997) update the list of large mergers from 1948 through 1988 and calculate three capital market measures of value creation. They facilitate "mergers for efficiency," rather than "merger for diversity." Wang and Wang (2005) provide an application model for merger evaluation in high-tech business. Their study tries to build a model to find the best merger candidate. Delmas and Tokat (2005) use DEA to analyze how the process of retail deregulation affects the comparative efficiency of governance structures, which range on a continuum from fully vertically integrated structures to market transactions.

Talluri and Baker (1996) propose a two-phase mathematical programming approach for effective partner selection in designing a venture capital (VC) by combining the DEA and technique with an integer programming model. Shao and Lin (2002) develop an approach to investigate the effects of Information Technology (IT) on the technical efficiency in a firm's production process. DEA and Tobit models are used to measure the efficiency scores upon the corresponding IT investments of the firms. To our best knowledge, there are no researches reported, that use DEA to select strategic alliance candidates in technology oriented business. The remaining of this paper is organized as follows; two DEA models are reviewed followed by the development of the DEA-based heuristic method for strategic alliance candidate selection (ACS). Case study and the analysis are then demonstrated followed by the conclusion.

CONCEPT OF THE DEA METHODOLOGY

DEA was first proposed by Charnes et al. (1978) (CCR). Its original idea comes from the measurement model of production efficiency proposed by Farrell (1957). DEA itself is a non-parametric method for assessing the relative efficiency of decision making units (DMUs) based upon multiple inputs and outputs. The primitive DEA model adopts the concept of production in microeconomics: efficiency = output / input. Banker et al. (1984) (BCC) developed a new model from the CCR model to understand the problems of pure technical efficiency (PTE) and scale efficiency (SE). Both of the CCR and BCC models are summarized as follows.

CCR model

The CCR model intends to maximize the ratio of weighted outputs against weighted inputs. It reduces multiple outputs to a single "virtual" output, and multiple inputs to a single "virtual" input for each DMU. CCR is good at analyzing the relative efficiency without setting the weights in prior, which makes the CCR model more objective. Assume that there are n DMU. Each DMU has m inputs and s outputs. Let x_{ij} represent the ith input and y_{rj} represent the rth output of DMU j, respectively. Let u_r and v_i represent the virtual variables of rth output and ith input, respectively. Let h_j represent the relative efficiency of DMU j. Where ε is a relatively small positive number (normally set at 10^{-6}). The relative efficiency of each DMU can be calculated by solving the following mathematical programming problems:

Max $$h_j = \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \tag{1}$$

Subjected to $$\frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \le 1 \tag{2}$$

$u_r \geq \varepsilon > 0$ (3)

$v_i \geq \varepsilon > 0$ (4)

r =1,2,3,….,s ; i =1,2,3,…..,m ; j =1,2,3,…..,n

The CCR input model can suggest improvement directions and the values of both outputs and inputs in order to achieve the desired efficiency value of 1, which can be done by calculating the following equations:

$$x_{ij}^{*} = h_j x_{ij} - s_i^{-*}, \quad i = 1,\ldots,m \tag{5}$$

$$y_{rj}^{*} = y_{rj} + s_r^{+*}, \quad r = 1,\ldots,s \tag{6}$$

Where s_i^- represents the lacking quantity (slack) of the output and s_r^+ represents the redundant quantity (surplus) of the input. x^*_{ij}, y^*_{rj}, s_r^{+*} and s_i^{-*} represent the optimal values of x_{ij}, y_{rj}, s_r^+ and, respectively. Note that when the value of objective function h_j = 1, s_r^+ =0 and s_i^- =0 (for all r and i). That is, DMU j achieves its optimal efficiency. Note that, CCR is the most popular DEA model for evaluation of the total operational efficiency.

BCC model

The difference between the CCR and BCC models is the use of returns-to-scale. For each DMU, BCC allows variable returns-to-scale, while CCR is characterized by constant returns-to-scale. The BCC model has an additional convexity condition. The input–oriented BCC model can be written as:

$$\text{Max} \quad h_j = \frac{\sum_{r=1}^{s} u_r y_{rj} - u_0}{\sum_{i=1}^{m} v_i x_{ij}} \tag{7}$$

$$\text{Subjected to} \quad \frac{\sum_{r=1}^{s} u_r y_{rj} - u_0}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1 \tag{8}$$

$$u_r \geq \varepsilon > 0 \tag{9}$$

$$v_i \geq \varepsilon > 0 \tag{10}$$

r =1,2,3,…,s ; i =1,2,3,…,m ; j =1,2,3,…,n

u_0 is a real number to indicate the intercept of the production frontier. When u_0 >0, the production frontier for this DMU is decreasing returns-to-scale (DRS). When u_0 =0, the production frontier for this DMU is constant returns-to-scale (CRS). When u_0 <0, the production frontier for this DMU is increasing returns–to-scale (IRS). In addition, the suggested improvement directions of the BCC input model are the same as the CCR input model.

ALLIANCE CANDIDATE SELECTION (ACS) METHODOLOGY

Based on the DEA method, this paper proposes a heuristic method to select strategic alliance candidates' efficiency in biotechnology industry. This paper uses the CCR model for the calculation of strategic alliance. The ACS methodology can be divided into four stages; these are data collection, variables setting, calculation, and analysis, as shown in Figure 1. Details are described as follows.

Data collection

There are five steps in the data collection stage, whose output is the DMU data table for the calculation of Part C.

Step A-1: DMU Selection

Select DMU companies which have at least one of the following features related to our target company:

1. Business connection or potential connection with our target company;
2. Competitors;
3. Upstream or downstream of the industry.

Step A-2: Input/Output factors setting

Find the dominating input resources which dominate the performance. Determine the major performance indicators. The selection of input resources and performance indicators can be from the following ways:

1. Industrial forum
2. Survey
3. Brainstorming of industrial managers

ACS can remove the redundant items, so there are no constraints on the amount of inputs and outputs (I/O). Anything important or potentially important can be included. The characteristics of I/O items can be multilateral. The items can have different units.

Step A-3: Original raw data collection

Find the input resources and output outcomes data for all

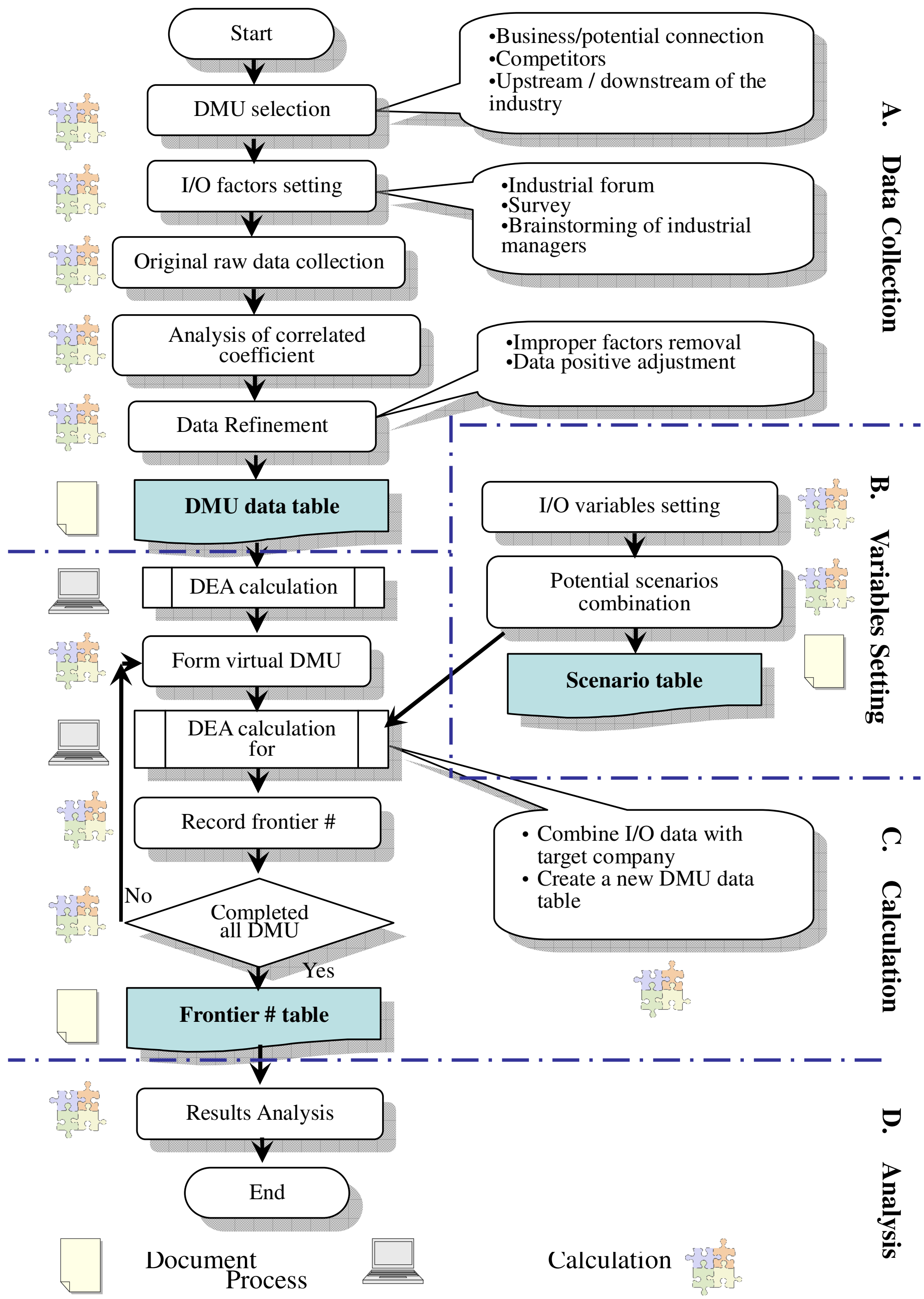

Figure 1. Procedures of alliance candidate selection (ACS).

Step A-4: Correlation analysis

Calculate the correlation coefficient for those raw data of all DMUs.

Step A-5: Raw data refinement

The screening and exclusion of non-effective data are done in this step, such that all the remaining data are positively correlated between the inputs and the outputs. Both within the inputs and the outputs, if the correlation coefficient between any two factors is very high, like more than 0.85, these two factors are redundant and one of them can be removed. Moreover, when the coefficient between input and output is very low, like low than 0.15, the two factors are low correlation and one of these factors can be removed. The removing steps continue until there are no data to be removed. When some data are removed, note that each time the correlation analysis step (Step A-3) is invoked to update the correlation coefficients. Finally, the DMU Data table is the outcome of the data collection stage.

Variables setting

Two steps are under variables setting. After the completed steps, the outcome is scenario table, which record scenario characteristics for calculation of the variables setting.

Step B-1: Input/Output variable setting

Since it always would have some changes following the formation of the alliance, we set up 2 parameters to modify the changes in input and output. The purpose of parameter 'k' is for the modification of the sum of input factors, and parameter 'm' is for the modification for sum of output factors. For example, we assume the alliance can obtain the advantage of input resources by reducing 20% (k=0.8, this means we sum input resources for two merged companies then multiply 0.8), or obtain the advantage of output resources by increasing 20% (m = 1.2, this means we sum input resources for two merged companies, then multiply 1.2).

Step B-2: Potential scenarios combination

Then, combining all inputs and outputs by two parameters, list the total combination scenarios.

Outcome: Scenario table

List the total scenarios form a scenario table.

Calculation

Five steps make up this calculation. After completing the steps, the outcome is frontier number table, which is used for analysis of the potential performance of virtual alliances in the calculation.

Step C-1: DEA Calculation

According to CCR model, use DMU Data Table to calculate the company efficiency ranking before the formation of the alliance. The purpose is to understand the performances of all DMUs before the alliance is formed.

Step C-2: Form virtual DMU

Merge the inputs and outputs one by one between the i DMU and target company to be the virtual alliance. The 'i' is an integer. Replace data of i DMU with data from the virtual alliance in DMU Data Table.

Step C-3: DEA Calculation for all scenarios

The data of virtual alliance in DMU Data Table are multiplied by the parameters for first combination scenario in the scenario table. Then, use DEA to calculate the efficiency ranking. If the virtual alliance is frontier, then record in the frontier number table. Afterwards, the data of virtual alliance in DMU data table are multiplied by the parameters for second combination scenarios. Repeat the DEA calculation to record the frontier number, and so on, till all scenarios are complete.

Step C-4: Check all DMU are completed steps 2 and 3

Let 'i' is changed to 'i+1' and go back to step 2, until every DMU has formed a virtual alliance.

Outcome: Frontier number table

Summarize the frontier number for all virtual alliances as the frontier number table.

Analysis

Under evaluation with multiple scenarios, Norman and Stoker (1991) proposed a suitable method for testing. When doing the DEA evaluation, the DUMs in frontier means these companies have the best efficiency.

Therefore, a DMU becomes a frontier in more different scenarios, and we assume it could have more opportunity to be the most efficient company. The ranking of efficiency integrated several scenarios would be ranked by the frontier numbers. Compare the results before and after the formation of the alliance of target company to analyze the differences. Find out the most successful opportunity for the virtual alliances.

CASE STUDY – TAIWAN BIOTECHNOLOGY INDUSTRY

To implement the ACS model, this paper selects one target company and 19 candidates for analysis. All data are collected from Taiwan Stock Exchange Post System. Details are depicted as follows.

Data collection

A win-win supplier-buyer model is vital for competitive- ness (Cho and Soh, 2010). The strategic target company is a real company that wants to find its strategic alliance candidate. Therefore, this paper collects 19 candidate companies which are related to the company following the step of ACS. According to discussion with many managers in this industry, this paper summarized major concerns of strategic alliance. These concerns are low cost, less employees and high profit. According to these requirements, the

Table 1. Original raw data of inputs and outputs.

Item	Input				Output			
	Capital	**Assets**	**Employee**	**RD**	**Revenue**	**Profit**	**EPS**	**Equity**
Unit	**Million**	**Million**	**Person**	**Million**	**Million**	**Million**	**NTD**	**Million**
A	331	546	102	27	279	17	0.32	467
B	632	2595	240	201	1576	303	3.75	1069
C	604	1204	209	43	1012	111	1.38	871
D	498	974	232	14	347	15	0.32	619
E	350	305	19	43	39	-26	-0.64	294
F	2710	5715	450	29	2487	206	3.01	4120
G	3742	6493	1024	187	4374	299	0.92	5162
H	3644	7285	2191	89	8903	107	0.71	4449
I	2417	5821	933	193	2809	717	2.99	5007
J	1281	3029	492	101	1452	324	1.66	1799
K	1705	3058	192	75	1976	686	3.53	2724
L	993	2983	86	87	2932	610	2.78	1469
M	9800	50772	602	18	9138	373	2.11	30988
N	360	104	58	33	32	-103	-3.89	86
O	300	496	71	59	36	-92	-2.94	205
P	850	2125	350	66	1555	79	6.44	1607
Q	431	846	86	31	774	138	2.95	715
R	680	3707	155	0	2040	71	2.18	2064
S	6181	9772	19	0	1122	-110	-0.38	6599
Target company	718	999	200	61	620	138	2.33	866

Table 2. Correlation analysis of original raw data.

	Capital	Assets	Employee	RD	Revenue	Profit	EPS
Capital	1						
Assets	0.8948	1					
Employee	0.3701	0.2295	1				
RD	-0.0633	-0.1288	0.4151	1			
Revenue	0.7486	0.7343	0.7750	0.1749	1		
Profit	0.1796	0.2181	0.2248	0.5714	0.3516	1	
EPS	0.0473	0.1002	0.1062	0.2805	0.2061	0.5655	1

Table 3. Correlation analysis after adjustment.

	Assets	Employee	Revenue	Profit
Assets	1			
Employee	0.2295366	1		
Revenue	0.7342894	0.7749449	1	
Profit	0.2180533	0.2248374	0.3515596	1

DEA input factors are set to be capital, assets, employee's number and research and development (R&D) expense. The output factors are set to be revenue, profit and earning per share (EPS). The original raw data are collected and shown in Table 1. The data source is from Taiwan Stock Exchange, Market Observation Post System (2010). Then, correlation analysis is used to analyze the improper factors. The correlation analysis for all factors is depicted in Table 2. Following the ACS's procedure, remove the factors with the negative coefficient (such as RD) and with very high (such as capital) or very low (such as ESP) coefficient value. After adjustment, re-execute the correlation analysis and new results are shown in Table 3. Obviously, the coefficients have no any violation,

Table 4. DMU Data table.

Item	Input		Output	
	Assets	Employee	Revenue	Profit
Unit	Million	Person	Million	Million
A	546	102	279	137
B	2595	240	1576	423
C	1204	209	1012	231
D	974	232	347	135
E	305	19	39	94
F	5715	450	2487	326
G	6493	1024	4374	419
H	7285	2191	8903	227
I	5821	933	2809	837
J	3029	492	1452	444
K	3058	192	1976	806
L	2983	86	2932	730
M	50772	602	9138	493
N	104	58	32	17
O	496	71	36	28
P	2125	350	1555	199
Q	846	86	774	258
R	3707	155	2040	191
S	9772	19	1122	10
Target company	999	200	620	258

so the final factors of inputs and outputs are fixed to be “Assets”, “Employee”, “Revenue” and “Profit”.

Therefore, remove some of the improper factors, the final DMU data table is shrunk to include only 2 inputs and outputs each.

According to the assumption of DEA, all values of raw data need to be positive, but the output factor, profit, has negative values in some DMUs.

Therefore, following the DEA method, this research adds120 million for all DMUs’ profit to adjust the data, and then DEA might start to work. The final DMU data table is then changed to Table 4.

Variable setting

Following the ACS’s procedure, this paper assumes that the input resource could be reduced by 20% and output resources could be increased by 20%. Therefore, k is 0.8 which means we would sum the input resources for two strategic alliance companies then multiply by 0.8 and m is 1.2, which means we would sum the input resources for two strategic alliance companies then multiply by 1.2. The combinations of inputs and outputs are demonstrated in Table 5 with a total of 16 scenarios. These 2 parameters could be changed according to the expert’s assumption.

Calculation

First of all, execute the CCR for DMU data table, to understand the DMU performance ranking prior to the formation of the alliance. The results are shown in Table 6. Five companies have the best efficiency. They are E, H, L, Q, and S. Secondly, start to form a virtual company and execute a DEA calculation for every scenario. According to ACS’s procedures, each virtual company needs to run for 16 scenarios and in total there will be 19 virtual companies. Three hundred and four DEA calculations were conducted (16 * 19 = 304). This research summarizes the frontiers in the frontiers number table, which is depicted as Table 7. Since every virtual company has a total of 16 scenarios, the ‘Successful Chance’ is defined as the frontier number divided by 16 (total 16 scenarios). The successful chance is illustrated in Figure 2.

RESULTS ANALYSIS

Compared with the performance ranking before and after the formation of the alliance for all DMUs (Tables 6, 7 and Figure 2). Some major issues are summarized as follows: The company E, H, L, Q, and S are the best 5 efficiency rated companies before the formation of any strategic alliance. They are the best potential candidates for astrategic alliance. However, after ACS calculation, the results are different. After our calculation, the company H, L, and Q retain the first priority. These virtual companies have the highest opportunities (100%) to have the best efficiency following the formation of a strategic alliance.

The company A and K are both second priority. Both of their virtual companies have 12 frontiers. This means both of them have a 75% opportunity to retain the leading edge in this industry. The company E is third priority. Its virtual company has 11 frontiers. This means company E only has a 69% opportunity to remain the best and has the best efficiency prior to the formation of an alliance.

Table 5. Scenario table.

Scenario	Sum of capital * k	Sum of employee * k	Sum of revenue * m	Sum of profit * m
1	1	1	1	1
2	0.8	1	1	1
3	1	0.8	1	1
4	1	1	1.2	1
5	1	1	1	1.2
6	0.8	0.8	1	1
7	0.8	1	1.2	1
8	0.8	1	1	1.2
9	1	0.8	1.2	1
10	1	0.8	1	1.2
11	1	1	1.2	1.2
12	0.8	0.8	1.2	1
13	0.8	0.8	1	1.2
14	0.8	1	1.2	1.2
15	1	0.8	1.2	1.2
16	0.8	0.8	1.2	1.2

Table 6. DMU Performance ranking before alliance.

No.	DMU	Score	Rank
5	E	1	1
8	H	1	1
12	L	1	1
17	Q	1	1
19	S	1	1
11	K	0.9284006	6
20	Target company	0.8447962	7
3	C	0.8396367	8
1	A	0.8195542	9
16	P	0.6655952	10
2	B	0.6284619	11
7	G	0.6144914	12
18	R	0.553452	13
14	N	0.5335715	14
9	I	0.5121536	15
10	J	0.5121189	16
4	D	0.453699	17
6	F	0.4238099	18
13	M	0.4138679	19
15	O	0.1838214	20

Table 7. Frontier number table.

Company	Frontier number	Rank
H+Target Company	16	1
L+Target Company	16	1
Q+Target Company	16	1
A+Target Company	12	4
K+Target Company	12	4
E+Target Company	11	6
N+Target Company	8	7
C+Target Company	6	8
P+Target Company	2	9
B+Target Company	0	10
D+Target Company	0	10
F+Target Company	0	10
G+Target Company	0	10
I+Target Company	0	10
J+Target Company	0	10
M+Target Company	0	10
O+Target Company	0	10
R+Target Company	0	10
S+Target Company	0	10

Therefore, company E will have less desire to form an alliance, because it might reduce its performance.

The companies N, C and P are fourth priority and their virtual companies have the success chances of 50, 38, and 13%, respectively. Even though the results are not perfect, if we check the performance before the formation of an alliance from Table 6, we will find that these companies will experience great improvement through forming an alliance. This means they would have strong desire to form alliance. For other companies, where the frontier number is 0 after the formation of an alliance, this means they will have no chance to achieve the highest level of efficiency through an alliance. This research does not recommend these companies forming an alliance.

Besides, company S had the best ranking before forming of an alliance, but its virtual company has no chance to be perfect. This means a good company is not

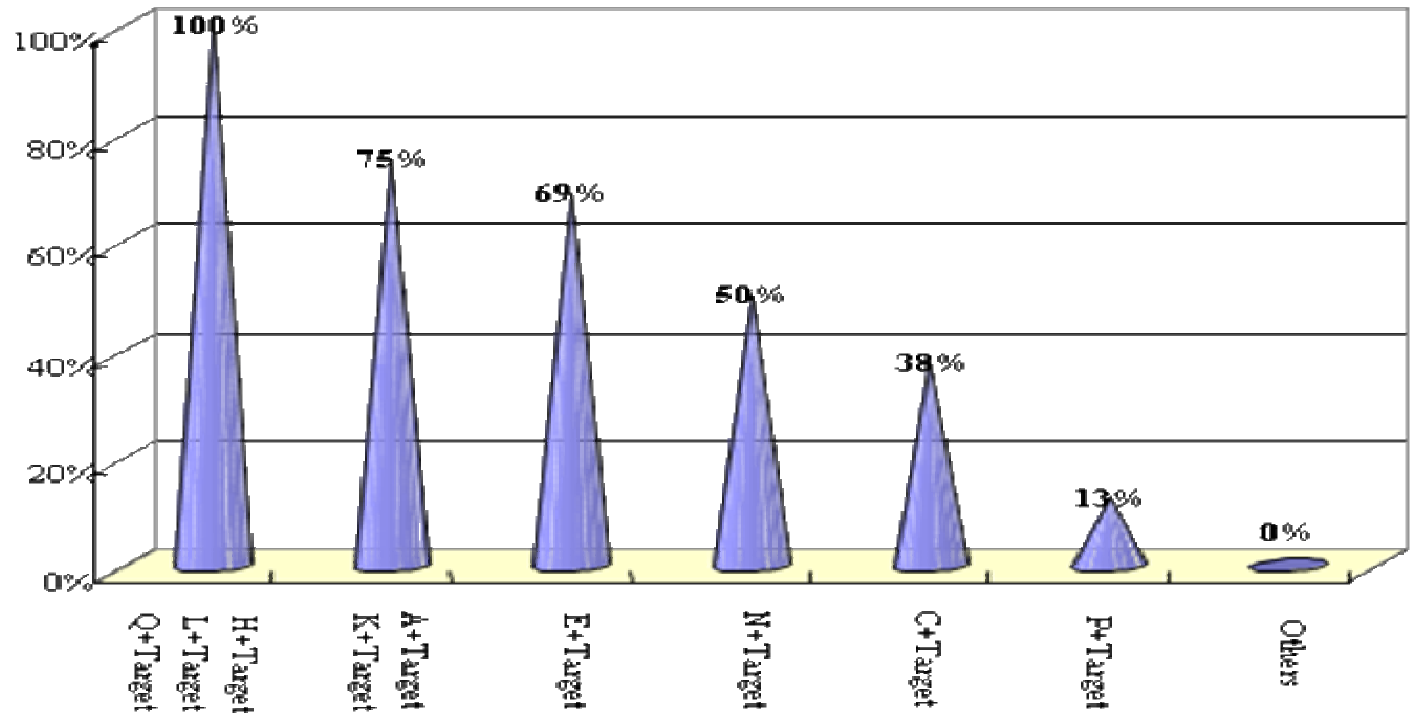

Figure 2. Successful chance.

always suitable for an alliance. Through calculation by ACS, a wrong combination alliance will be easy to distinguish. The method of ACS and the analysis are both discussed in a forum with several industrial managers (including the managers from target company) and their feedback was sound. Target company is planning to use ACS for their evaluation tool for partner selection of strategic alliance.

ACS is recognized to effectively provide all essential analysis and recommendations to enterprises for strategic alliance.

CONCLUSIONS

Biotechnology is the star industry of coming era. Strategic alliances have become a popular strategy for many biotech companies to extend their business roadmap. The objective of this paper is to develop an effective method to assist biotech companies in evaluating operation efficiency and finding the best candidate for a strategic alliance in complicated technology conditions. Its focus is on the realization of strategic plans and efficiency. According to ACS, candidates will be easy to separate into different priorities. This application design might help top management in their decision making process for business extension.

The results are sound for enterprises to find future candidates for a strategic alliance. Besides, academic researchers also can fully use this model to extend the applications of DEA for more diversities. Furthermore, selection of inputs and outputs are also more alternatives for study, such as research and development expenses, research and development manpower, etc. Future direction should be in the consideration of the involvement with intangible resources, for input factors or output factors, and analysis among different industries. Moreover, the trend of inputs and outputs could be discussed as well.

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