Efficiency Evaluation of Business in IoT Supply Chains by Network DEA

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Abstract

Recently Internet of things (IoT) and its applications are emerging as a momentous trend in industry. Numerous hardware and software providers have been entering the intense market competition in IoT related industries. Correspondingly, the attention on evaluation of IoT industry is growing. However, it is a main theme as how to consider the multiple dimensions and dependencies among the criteria in IoT supply chains simultaneously. By considering internal processes in DMUs as well as their interactions, this study designs the evaluation methods with network data envelopment analysis (NDEA) and multi-objective programming (MOP) techniques. This work intends to estimate the efficiency of IoT businesses from the perspectives of R&D, manufacturing, sales and finance, and the overall performance. The proposed models are implemented with empirical case studies in IoT supply chains in Taiwan. The results show the usefulness and validity of the proposed methods in evaluating IoT related business.

Keywords: IoT supply chains, Network Data Envelopment Analysis (NDEA), Multi-Objective Programming (MOP), Case study in Taiwan

1 Introduction

1.1 Background of IoT

Internet of things (IoT) [1-5] is the developing technology to connect smart devices to the Internet. Recently IoT and its applications are emerging as a momentous trend in industry. Numerous hardware and software providers have been entering the intense market competition in IoT services. Correspondingly the attention on evaluation of IoT industry is growing. It has been a key opportunity in 3C industry and many domains of application, e.g. healthcare, smart home, entertainment, manufacturing automation, energy management, payment, and so on. IoT has caught intensive attention due to its high potential to change the business and industrial processes and generate enormous economic value [6].

Regarding the frameworks and design for IoT services, Yang and Wei [4] propose to design the conversion scheme for communication protocols of IoT devices (IoT-CPCS). Their design aims to integrate the formats of the data collected by different IoT devices, convert these data into useful and important information, present the converted information in readable message formats, and consequently store these messages in virtual servers built in the cloud platform. Later Hung [5] proposes a model for improving the flexibility of sensors to enhance the intelligence of IoT. The proposed model defines the quality levels of events and monitoring data for all types of monitoring, wherein the data or events with different levels have different transmission priority. In the model application, the sensors shorten the event detection and reaction times. Consequently, the efficiency of monitoring is enhanced. Also, business models for IoT services [7] and investments and challenges for enterprises entering IoT are discussed [8].

From the perspectives of services, Kim and Kim [6] propose an AHP model for assessing the viability of IoT applications consisting of 11 technology, market, and regulation factors. Their model based on expert rating was applied to assess and compare the prospect of IoT healthcare, IoT logistics, and IoT energy management. The results showed that IoT logistics is the most promising IoT application. Security is another focus in IoT studies. At the same time, security [2] and energy efficiency [9] have their non- negligible position in the areas of IoT services.

Since IoT is leading to a paradigm shift in academia as well as industries, it is natural to examine IoT services and industry from a systematic view. The issue arises as how to consider the multiple dimensions and dependencies among the criteria in IoT supply chains simultaneously. This study intends to develop the evaluation model of IoT supply chains by integrating network DEA and multi-objective decision making methods. By considering the perspective from R&D, manufacturing, sales and finance, and their interactions as well as the overall performance, this study designs the evaluation framework with network DEA. Using multi-objective programming (MOP) techniques, the network data envelopment analysis (NDEA) model is formulated and solved. With empirical case studies, the link of the methods and applications in IoT related industries can be demonstrated and validated.

1.2 DEA and Network DEA

Data envelopment analysis (DEA) [10-13] has been widely used in assessing the relative efficiencies of decision making units (DMUs). In business practices, it is common to define the relative efiiciency as the ratio of weighted sum of outputs to weighted sum of inputs. The BCC model developed by Banker *et al*. [10] assesses the relative efficiencies of DMUs by extending the constant-returns-to-scale CCR model [12] to variable returns to scale. Consider n

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DMUs (j = 1, … , n) under assessment. Each DMU consumes m inputs (i = 1, …, m) and produces s outputs (r = 1, ..., s), denoted by X_{1j}, X_{2j}, ..., X_{mj} and Y_{1j}, Y_{2j}, ..., Y_{sj} respectively. The efficiency of DMU$_k$ can be computed by the BCC model as follows.

$$
\begin{aligned}
&Max \quad E_k = \frac{\sum_{r=1}^{s} u_r Y_{rk} - u_0}{\sum_{i=1}^{m} v_i X_{ik}} \\
&s.t. \\
&\qquad \frac{\sum_{r=1}^{s} u_r Y_{rj}}{\sum_{i=1}^{m} v_i X_{ij}} \le 1,\ j = 1, 2,\ \dots, n \\
&\qquad u_r, v_i \ge \varepsilon;\ r = 1, 2,\ \dots, s;\ i = 1, 2,\ \dots, m \\
&\qquad u_0 \text{ unrestricted in sign}
\end{aligned}
\tag{1}
$$

In (1) the obective function defines the relative efficiency that is the ratio of weighted sum of outputs to weighted sum of inputs. The first inequality as above sets the upper limit of all relative efficiencies to 1. In the BCC ratio model, the objective function E_k is maximized for every DMU$_k$ individually. In (1), X_{ik} and Y_{rk} are the i-th input and r-th output of DMU$_k$; u_r, v_i are the weights of the outputs and inputs, respectively; ε is a small positive threshold which ensures all weights to be nonnegative. When the intercept of the production function $u_0 > 0$, the efficiency frontier presents decreasing returns to scale; if $u_0 < 0$, it manifests increasing returns to scale; if $u_0 = 0$, the models turns out to be the constant returns to scale CCR model.

From the standpoint of decision making, evaluating a DMU involves examining its organization and process model from multiple perspectives. The departmental decision makers in an organization are expected to work collaboratively for common goals to maximize the overall DMU performance. Under such circumstances, the conventional DEA methods are insufficient to reflect the collaborative behaviors in a DMU.

Compared to conventional DEA models that operate by a black-box or a separation approach, network DEA [14-15] arises due to its competence in evaluating performance without neglecting internal interactions within DMUs. Recently, Tone and Tsutsui [16] proposed a general slack-based network DEA approach called Network SBM that can deal with intermediate products formally. Later, Tone and Tsutsui [17] develop a related dynamic DEA based on the slacks-based measure approach, called dynamic SBM (DSBM). Eventually, they extend their work into a dynamic DEA model involving network structure in each period by using a slacks-based measure approach [18]. Based on network SBM (NSBM) and dynamic SBM (DSBM) models that were previously published separately, Tone and Tsutsui propose a hybrid of these two models. Lim and Kim [19] proposed a two-stage dynamic network DEA model that can consider variable time lag effects, namely multiple carryover schemes, optimized for each DMU in efficiency measurements. Lu et al. [20] later employed dynamic three-stage network data envelopment analysis, considering parallel production in the agricultural and industrial sectors, to assess the impact of greenhouse gas emissions on the climate change and natural disaster stages. Tavassoli et a. [21] formulates a fuzzy network DEA (FNDEA) model for assessing the efficiency of Iran's electricity distribution network components with sustainability considerations and uncertain data. They also proposes a fuzzy linear programming model to determine the optimal lower bound for all input and output weights.

This study intends to develop evaluation methods by the network data envelopment analysis. By considering the internal processes of the IoT business, we design and solve the evaluation model by network data envelopment analysis and multi-objective programming techniques for IoT supply chains. The rest of this work is organized as follows. Section 2 addresses the problem statement and develops the network DEA models by using multi-objective programming. In Section 3, the empirical case studies are demonstrated. The discussions and concluding remarks are given in Section 4.

2 Problem and Model Formulation

Consider n companies in IoT supply chains (DMUs, j = 1, …, n) consisting of K divisions (k = 1, …, K). Let m_k and r_k be the numbers of inputs to and outputs from Division k, respectively. The notations of the parameters and variables are summarized in Table 1. Based on BCC models, this work develops the following network DEA method.

Table 1. Parameters and variables

n	Number of DMUs
K	Number of departments (functions)
r_k	Number of outputs from department k
m_k	Number of inputs to department k
(k, h)	The link from department k to department h
L	The set of inter-department links
X_{ij}^{k}	The i-th input to department k at DMU$_j$
Y_{rj}^{k}	The r-th output from department k at DMU$_j$
$Z_{jp}^{(k,h)}$	The p-th link from department k to department h at DMU$_j$
$\phi_{(k,h)}$	The number of links from department k to department h

2.1 The NDEA-MOP Model

In the network DEA model, the efficiencies of a DMU and its subunits (divisions) are evaluated cohesively. Figure 1 shows an example of using the NDEA approach.

This study denotes the link streaming from Division k to Division h by (k, h) and the set of links by L. The input resources to DMU$_j$ at Division k are $\{\boldsymbol{x}_j^k \in R_+^{m_k}\}$ (j = 1, ..., n; k = 1, ..., K); the output products from DMU$_j$ at Division k are $\{\boldsymbol{y}_j^k \in R_+^{r_k}\}$ (j = 1, ..., n; k = 1, ..., K); the linking intermediate products from Division k to Division h are $\{\boldsymbol{z}_j^{(k,h)} \in R_+^{\phi(k,h)}\}$ (j = 1, ..., n; $(k,h) \in L$) where $\phi_{(k,h)}$ is the number of items in Link (k, h). The NDEA-MOP model is formulated as (2)-(4).

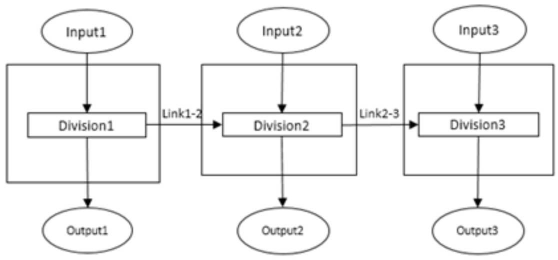

Figure 1. The NDEA model [16]

NDEA-MOP

$$Max \quad E_o^k = \frac{\sum_{r=1}^{r_k} u_r^k Y_{ro}^k + \sum_{\forall(k,h)} \sum_{p=1}^{t_{(k,h)}} \mu_h^k Z_{op}^{(k,h)} - \alpha_k}{\sum_{i=1}^{m_k} v_i^k X_{io}^k + \sum_{\forall(g,k)} \sum_{q=1}^{t_{(g,k)}} \omega_g^k Z_{oq}^{(g,k)}} \qquad k = 1,...,K. \quad \textbf{(2)}$$

s.t.

$$\frac{\sum_{r=1}^{r_k} u_r^k Y_{rj}^k + \sum_{\forall(k,h)} \sum_{p=1}^{t_{(k,h)}} \mu_h^k Z_{jp}^{(k,h)} - \alpha_k}{\sum_{i=1}^{m_k} v_i^k X_{ij}^k + \sum_{\forall(g,k)} \sum_{q=1}^{t_{(g,k)}} \omega_g^k Z_{jq}^{(g,k)}} \le 1 \ , k=1,...K; j = 1,..., n. \quad \textbf{(3)}$$

$$\sum_{i=1}^{m_k} v_i^k X_{io}^k + \sum_{g=1}^{t_{(g,k)}} \omega_g^k Z_{ro}^{(g,k)} = 1 \ , k=1,...K. \quad \textbf{(4)}$$

$$u_r^k, v_i^k, \mu_h^k, \omega_g^k, w_k \ge \varepsilon > 0, \ \alpha_k \text{ unrestricted in sign}$$

$$r = 1,2,\dots,r_k; i = 1,2,\dots,m_k; all \ (k,h),(g,k) \in L$$

where u_r^k, v_i^k, are the weights of outputs and inputs of department k, respectively, μ_h^k, ω_g^k are the weights of intermediate products (links) outgoing from k to h and incoming from g to k, respectively, and ε is a very small positive number constituting the lower bound of all weights.

In the NDEA-MOP model, K objective functions are defined for the departmental efficiency E_o^k (k = 1,...K) as in (2). The constraints (3) set the upper limit of all relative efficiencies to 1. The constraint (4) turns the NDEA-MOP into a linear model for feasibility in finding the optimal solutions. Notably, the NDEA-MOP is designed as a cooperative model; that is, the strategic resources are allocated collaboratively by each functional department, as is the DMU decision level.

2.2 The Solution Process

Many techniques have been proposed for solving multi-objective programming problems [22-26], and some of them are inspired by Zimmermann's fuzzy approach [27]. This study develops the solution process for NDEA-MOP based on Zimmermann's approach. The details for solution steps are described as below.

Step 1: Get the ideal solution of each objective.

To obtain the ideal solution, each objective is optimized independently regardless of other objectives. For DMUo, we maximize every E_o^k to acquire its ideal objective value E_o^{k*} individually.

Step 2: Get the anti-ideal solution of each objective.

To obtain the anti-ideal solution, each objective is computed in the opposite way regardless of other objectives. For DMUo, we minimize every E_o^k to acquire its ideal objective value E_o^{k-} , individually.

Step 3: Define the membership function of each objective by its ideal and anti-ideal solutions as below.

$$\mu_{E_o^k}(E_o^k) = \frac{E_o^k - E_o^{k^-}}{E_o^{k^*} - E_o^{k^-}}. \quad \textbf{(5)}$$

The membership function evaluates the fulfillment level of each objective.

Step 4: Get the final solution.

The final solution can be found by maximizing the total satisfaction level in two ways: Compensatory and non-compensatory solutions.

Compensatory Solution

$$Max \quad \lambda = \sum_{k=1}^{K} w_k \mu_{E_o^k}(E_o^k). \quad \textbf{(6)}$$

$s.t.$ (3)-(5)

where λ is the mean value of all divisional efficiencies to be maximized.

Non-compensatory Solution

$$Max \quad \lambda$$

$s.t.$ (3)-(4)

$$\lambda \le \mu_{E_o^k}(E_o^k) = \frac{E_o^k - E_o^{k-}}{E_o^{k*} - E_o^{k-}} \qquad k = 1,2,\dots,K. \quad \textbf{(7)}$$

where λ is the minimum of all divisional efficiencies to be maximized. Considering the self-controlling and non-compensatory natures in the internal process between the departments, this study uses the non-compensatory approach as (7) in solving the NDEA-MOP model. The flowchart of solution processes is depicted as Figure 2, where the functional department of DMUo can be evaluated simultaneously, and the overall efficiency score for DMUo is calculated as the average of all departmental efficiencies.

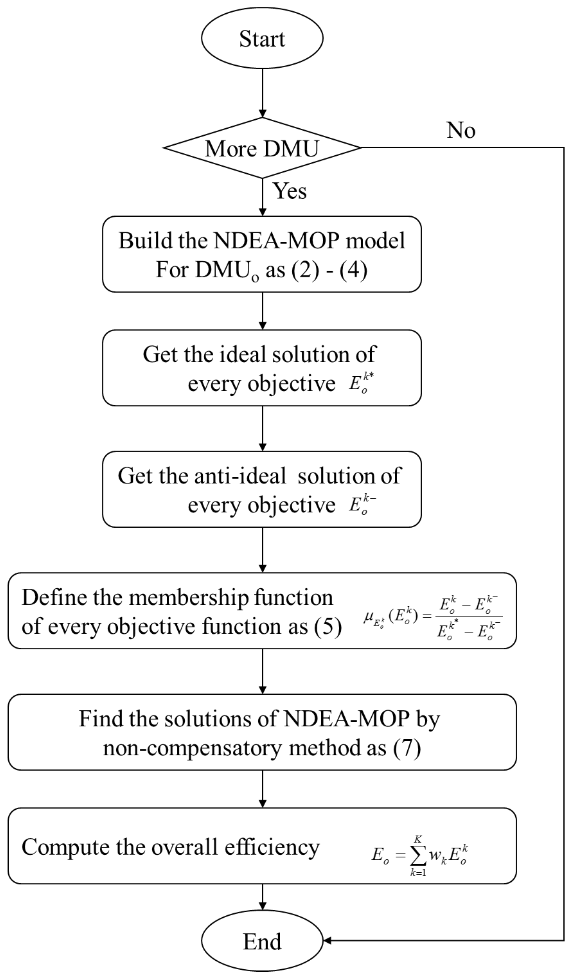

Figure 2. The flowchart for efficiency evaluation

3 Case Study

This study evaluates 30 listed companies in Taiwan IoT supply chains of automotive electronics and smart healthcare business. Notably, most of these samples have diversified investments in various product lines and services, not limited to IoT. The 30 businesses are classified according to their positions in the three layers of IoT supply chains [1] as in Table 2, where A means upstream (perceptiona layer), B means middlestream (netowrk layer), and C means downstream (applicaiton layer) in the IoT supply chain. In each DMU (company), three functions (departments) are analyzed: *research and development* (R&D), *manufacturing* (manufacture), and *sales and finance* (Sales & finance). The inputs, outputs and links are collected from the annual reports for the fiscal years 2015 to 2020. All monetary values are measured in 100 millions (100 M) NT dollars, except that patents are converted to points. Some of the factors are adjusted by adding a suffucient number to avoid zero and negative values in the network DEA.

This study formulate the structure and NDEA model based on general high tech business process that is also the base for business application systems, e.g. enterprise resources planning (ERP), management information systems (MIS), and so on. The business in high tech industry share similar process and operations. The factors we choose are what most stakeholders (management, employee, shareholders, customers, etc.) concern. The deparments and factors for evaluation are summarized as follow.

R&D department
Inputs: R&D expense
Link: intangible assets (outgoing)
Output: patent
Manufacture department
Inputs: plant and equipment, cost of goods sold (COGS)
Links: intangible assets (incoming), production (outgoing)
Sales and finance
Inputs: sales and administration cost
Link: production (incoming)
Outputs: revenue, profit, earnings per share

Among the factors as mentioned above, the intangible assets include patents, copyrights, franchises, goodwill, trademarks, etc.; the patents are the patents filed in Taiwan patent search systems [28] and Patent and Trademark Office (USPTO) patent database [29]. The structure of evaluatiion is depicted as Figure 3.

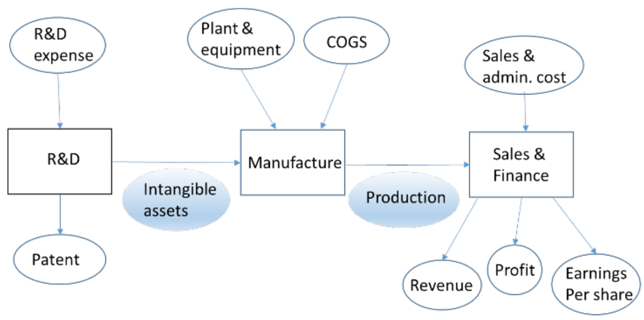

Figure 3. The NDEA model for IoT industry

Table 2. Classification of the DMUs**

DMU		DMU		DMU	
1	A	11	ABC	21	A
2	A	12	A	22	AB
3	AB	13	A	23	A
4	ABC	14	A	24	ABC
5	A	15	ABC	25	ABC
6	ABC	16	A	26	ABC
7	ABC	17	A	27	ABC
8	ABC	18	ABC	28	A
9	ABC	19	AC	29	A
10	ABC	20	A	30	A

** A: upstream (perceptiona layer),
B: means middlestream (netowrk layer),
C: means downstream (applicaiton layer)

By the MOP for NDEA designed in 2.1, this study computes the efficiency for the 30 companies in IoT supply chains. The results from the non-compensatory approach are obtained and compared by using LINGO 12.0 [30] as the solver. The overall efficiencies of the DMU are shown in Table 3; the departmental efficiencies of R&D, manufacturing and sales and finance are shown in Table 4 to Table 6, respectively.

Table 3. Overall efficiency of IoT DMU

	2015	2016	2017	2018	2019	2020
1	0.5186	0.7734	0.6344	0.7285	0.6806	0.7158
2	0.7009	0.5959	0.7861	0.6083	0.5732	0.5792
3	0.7194	0.8744	0.8189	0.5313	0.8892	0.8815
4	**1.0000**	0.6421	0.5903	0.8291	0.6654	0.6650
5	0.7024	0.8598	0.9687	**1.0000**	0.9325	0.9107
6	**1.0000**	**1.0000**	**1.0000**	**1.0000**	0.6720	0.6874
7	**1.0000**	**1.0000**	**1.0000**	**1.0000**	0.6610	0.6526
8	0.4425	0.8257	0.6833	0.4675	0.5834	0.5941
9	0.6755	0.4096	0.7615	0.3833	0.6686	0.6683
10	0.5316	0.6421	0.5231	0.3965	0.5659	0.5759
11	0.5368	0.6399	0.7403	0.4494	0.6100	0.6095
12	0.5155	0.7608	0.9064	0.7013	0.6389	0.6512
13	0.8504	0.8072	0.6483	0.6654	0.6767	0.6925
14	0.5250	0.6555	0.8562	0.4484	0.5669	0.5320
15	0.4198	0.8307	0.6788	0.8334	0.5436	0.5142
16	0.2943	0.6365	0.6878	0.4783	0.6223	0.5513
17	0.4808	0.5587	0.6163	0.6159	0.5340	0.5084
18	0.5485	0.6087	0.7513	0.454	0.6417	0.6140
19	0.5215	0.7612	0.8570	0.2273	0.6765	0.6777
20	0.4393	0.8867	0.9618	0.5298	0.9819	0.8337
21	0.5121	0.5187	0.6916	0.7620	0.5294	0.5268
22	0.5736	0.6546	0.5183	0.6643	0.6519	0.5976
23	0.4132	0.7148	0.5211	0.6752	0.5939	0.6637
24	0.4821	0.5966	0.6501	0.6153	0.5460	0.5734
25	0.3447	0.8538	0.6329	0.7288	0.5874	0.5978
26	0.2178	0.6648	0.7407	0.5429	0.5179	0.4995
27	0.6192	0.6265	0.4335	0.4585	0.5897	0.5648
28	0.7428	0.6717	0.7048	0.612	0.6698	0.6085
29	0.3027	0.6894	0.7418	0.4185	0.6580	0.6228
30	0.7368	0.7771	0.7935	0.7272	0.6981	0.6576
Max	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**0.9819**	**0.9107**
Min	**0.2178**	**0.4096**	**0.4335**	**0.2273**	**0.5179**	**0.4995**
Avg	**0.5789**	**0.7205**	**0.7300**	**0.6184**	**0.6476**	**0.6342**
Std	**0.2029**	**0.1383**	**0.1472**	**0.1921**	**0.1112**	**0.1008**

Figure 4 shows the distribution of overall efficiencies of business in IoT supply chains. From Table 7 and Figure 4, the overall efficiencies of IoT supply chains reveal multimodal. The modes of overall efficiencies shifted from [0.7, 0.8999] to [0.5, 0.6999] in 2019-2020. Among the business, DMU 6 and 7 reveal the full efficiencies in overall and all departments in 2015-2018. From 2019-2020, the efficiencies diminished due to the recession of IoT demands (as in Table 3).

Table 4. R&D efficiency of IoT DMU

	2015	2016	2017	2018	2019	2020
1	0.1713	0.7168	0.5434	0.6079	0.3548	0.6582
2	0.3867	0.2902	0.3849	0.2574	0.0712	0.1452
3	0.7966	0.9880	0.8189	0.6114	0.9869	0.9926
4	**1.0000**	0.4571	0.6824	0.9157	0.4248	0.4610
5	0.5814	**1.0000**	**1.0000**	**1.0000**	**1.0000**	0.9021
6	**1.0000**	**1.0000**	**1.0000**	**1.0000**	0.0597	0.0783
7	**1.0000**	**1.0000**	**1.0000**	**1.0000**	0.0173	0.0306
8	0.1917	0.8890	0.1635	0.2950	0.0246	0.0396
9	0.4512	0.1472	0.2845	0.9498	0.0058	0.0050
10	0.2993	0.4194	0.2020	0.5144	0.1554	0.2314
11	0.2044	0.2450	0.3398	0.2770	0.0387	0.0565
12	0.1820	0.6285	**1.0000**	0.3370	0.0856	0.1523
13	0.8989	0.7284	0.1949	0.2363	0.0797	0.1039
14	0.1880	0.3369	0.9921	0.1958	0.0326	0.0529
15	0.2624	0.9992	0.8685	**1.0000**	0.0337	0.0583
16	0.1969	0.1781	0.2544	0.3219	0.0249	0.0390
17	0.2201	0.5311	0.4226	0.3458	0.0135	0.0310
18	0.5214	0.7453	0.2994	0.1130	0.0444	0.0602
19	0.8698	0.3294	0.5711	0.3449	0.1381	0.1718
20	0.4095	0.8588	0.9915	0.5714	**1.0000**	**1.0000**
21	0.4649	0.4562	0.5677	0.6956	0.0323	0.0586
22	0.1211	0.2486	0.5459	0.3045	0.1282	0.1634
23	0.6292	0.8714	0.1786	0.4039	0.1036	0.4629
24	0.1443	0.1921	0.4760	0.2111	0.0218	0.0353
25	0.2414	0.9044	0.2194	0.5085	0.0348	0.0753
26	0.3535	0.5052	0.7916	0.1118	0.0143	0.0292
27	0.7323	0.1118	0.1056	0.1454	0.0143	0.0215
28	0.5492	0.3477	0.1144	0.7752	0.0094	0.0278
29	0.1866	0.1534	0.2253	0.2184	0.1400	0.2130
30	0.3706	0.3923	0.4963	0.2563	0.1147	0.1503
Max	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Min	0.1211	0.1118	0.1056	0.1118	0.0058	0.0050
Avg	0.4542	0.5557	0.5245	0.4842	0.1735	0.2169
Std	0.2880	0.3090	0.3154	0.3009	0.2944	0.2946

Looking into the departmental efficiencies, the R&D reached the high in 2016-2017 and gradually descended in 2018-2020 (as in Table 4). However, the efficiencies of manufacturing have maintained at [0.8, 0.95] from 2016 to 2020 (as in Table 5). As for the sales and finance, the efficiencies are sub efficient as [0.7, 0.83] except in 2015 and 2018 (as in Table 6).

Table 5. Manufacturing efficiency of IoT DMU

	2015	2016	2017	2018	2019	2020
1	0.6495	0.8338	0.9333	**1.0000**	0.9536	0.6808
2	0.9800	0.9295	0.9738	0.9659	0.9924	0.8821
3	0.7859	0.9880	0.8189	0.6114	0.9869	0.9397
4	**1.0000**	0.9122	0.9884	0.8750	0.9678	0.9553
5	0.8980	0.9593	0.9061	**1.0000**	0.7991	0.9150
6	**1.0000**	**1.0000**	**1.0000**	**1.0000**	0.9750	0.9839
7	**1.0000**	**1.0000**	**1.0000**	**1.0000**	0.9828	0.9636
8	0.8051	0.9473	0.9639	0.9693	0.8719	0.9006
9	0.6813	0.1000	**1.0000**	0.1000	**1.0000**	**1.0000**
10	0.8347	0.9477	0.9284	0.1000	0.9559	0.9262
11	0.9104	0.9343	0.9182	0.5897	0.9565	0.8899
12	0.9876	0.9545	0.9721	0.9453	0.9967	0.9400
13	0.9790	0.9939	0.9165	0.8998	0.9504	0.9869
14	0.9523	0.9741	0.9982	0.9426	**1.0000**	0.8824
15	0.8627	0.8396	0.8037	0.9049	0.9342	0.8739
16	0.5704	0.9651	0.9974	0.3903	0.9723	0.8904
17	0.7622	0.7359	0.9247	0.9171	0.9949	0.9003
18	0.9409	0.9509	0.9580	**1.0000**	0.9150	0.8848
19	0.5946	0.9543	**1.0000**	0.1489	0.8913	0.8611
20	0.1044	0.9402	0.8938	0.9179	0.9457	0.9005
21	0.2879	**1.0000**	0.8346	0.9514	0.8723	0.9260
22	0.8353	0.9714	0.8676	0.9134	0.9888	0.8529
23	0.1148	0.5734	0.8885	0.9798	0.9316	0.7939
24	0.7808	**1.0000**	0.9297	0.9825	0.9582	**1.0000**
25	0.1881	0.9794	0.9357	0.9023	0.9820	**1.0000**
26	0.1424	0.9247	0.9271	0.9990	0.9339	0.8912
27	0.8096	0.8961	0.9564	**1.0000**	0.8488	0.9237
28	**1.0000**	0.6927	**1.0000**	0.9610	**1.0000**	0.8499
29	0.6215	0.9149	**1.0000**	0.1895	0.9311	0.8551
30	0.8399	0.9389	0.8841	0.9253	0.9795	0.8404
Max	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Min	0.1044	0.1000	0.8037	0.1000	0.7991	0.6808
Avg	0.7306	0.8917	0.9373	0.8027	0.9490	0.9030
Std	0.2862	0.1784	0.0570	0.2999	0.0498	0.0669

Table 6. Sales & finance efficiency of IoT DMU

	2015	2016	2017	2018	2019	2020
1	0.7350	0.7696	0.4266	0.5777	0.7335	0.8085
2	0.7362	0.5681	0.9995	0.6016	0.6561	0.7103
3	0.5756	0.6471	0.8189	0.3711	0.6938	0.7123
4	**1.0000**	0.5569	0.1000	0.6966	0.6037	0.5787
5	0.6277	0.6201	**1.0000**	**1.0000**	0.9983	0.9150
6	**1.0000**	**1.0000**	**1.0000**	**1.0000**	0.9814	**1.0000**
7	**1.0000**	**1.0000**	**1.0000**	**1.0000**	0.9828	0.9636
8	0.3307	0.6408	0.9225	0.1383	0.8536	0.8420
9	0.8939	0.9817	**1.0000**	0.1000	**1.0000**	**1.0000**
10	0.4607	0.5591	0.4388	0.5751	0.5865	0.5700
11	0.4955	0.7404	0.9628	0.4814	0.8349	0.8822
12	0.3771	0.6994	0.7472	0.8214	0.8344	0.8613
13	0.6734	0.6994	0.8336	0.8601	**1.0000**	0.9869
14	0.4347	0.6556	0.5784	0.2067	0.6681	0.6608
15	0.1343	0.6535	0.3643	0.5954	0.6630	0.6103
16	0.1157	0.7663	0.8115	0.7228	0.8697	0.7244
17	0.4600	0.4092	0.5015	0.5849	0.5937	0.5939
18	0.1831	0.1298	0.9967	0.2489	0.9655	0.8971
19	0.1000	**1.0000**	**1.0000**	0.1880	**1.0000**	**1.0000**
20	0.8040	0.8611	**1.0000**	0.1000	**1.0000**	0.6005
21	0.7835	0.1000	0.6725	0.6390	0.6834	0.5959
22	0.7643	0.7437	0.1414	0.7749	0.8388	0.7765
23	0.4955	0.6996	0.4964	0.6420	0.7465	0.7344
24	0.5213	0.5976	0.5445	0.6523	0.6581	0.6849
25	0.6046	0.6775	0.7434	0.7756	0.7454	0.7181
26	0.1574	0.5646	0.5035	0.5179	0.6056	0.5781
27	0.3156	0.8717	0.2384	0.2300	0.9061	0.7491
28	0.6792	0.9749	**1.0000**	0.1000	**1.0000**	0.9479
29	0.1000	**1.0000**	**1.0000**	0.8475	0.9031	0.8003
30	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	0.9822
Max	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Min	0.1000	0.1000	0.1000	0.1000	0.5865	0.5700
Avg	0.5520	0.7063	0.7281	0.5683	0.8202	0.7828
Std	0.2893	0.2309	0.2895	0.2397	0.1521	0.1488

Comparing the departmenal efficiencies in IoT supply chains in Table 4 to Table 6, the manufacturing is most efficient, finance and sales is the second, and R&D is least efficient. Notably the average score of R&D grew from 2015 (0.4542) to 2016 (0.5557) and then ran down significantly in 2018 (0.4842) to 2019 (0.1735), and slightly grew in 2020 (0.2169).

Comparing the overall efficiencies of various sections in IoT supply chains in Table 8, AB shows the efficiencies during the recent 3 years, especially in 2019-2020; A and ABC show sub efficient. From Table 8, DMUs in AB revealed higher efficiencies in R&D and satisfactory scores in manufacturing; A and A BC showed advantages in sales & finance and manufacturing, respectively. All sections show satisfactory scores in manufacturing.

Table 7. Distribution of overall efficiency in IoT supply chains

	2015	2016	2017	2018	2019	2020
1	3	2	5	3	0	0
0.9~0.9999	1	7	3	2	2	1
0.8~0.8999	5	5	8	5	1	2
0.7~0.7999	2	10	9	7	0	1
0.6~0.6999	9	4	4	3	15	13
0.5~0.5999	6	1	1	7	12	12
0.4~0.4999	2	0	0	2	0	1
0.3~0.3999	2	0	0	1	0	0

Table 8. Average efficiencies over recent years

	A	AB	ABC
Overall	**0.6586**	**0.7027**	**0.6110**
2018	0.6408	0.5978	0.6276
2019	0.6883	0.77057	0.6041
2020	0.6467	0.7396	0.6013
R&D	**0.3162**	**0.5312**	**0.2337**
2018	0.4445	0.4580	0.5417
2019	0.2187	0.5576	0.0684
2020	0.2855	0.5780	0.0909
Manufact.	**0.8940**	**0.8822**	**0.8948**
2018	0.8561	0.7624	0.8017
2019	0.9514	0.9879	0.9448
2020	0.8745	0.8963	0.9379
Sales & fin.	**0.7447**	**0.6945**	**0.6977**
2018	0.6217	0.5730	0.5393
2019	0.8322	0.7662	0.7789
2020	0.7802	0.7444	0.7749

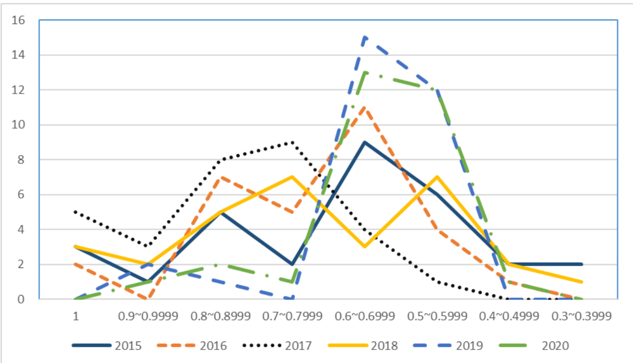

Figure 4. The distribution of overall efficiency of business in IoT supply chains

4 Conclusion

This study develops the NDEA-MOP model to evaluate the business in IoT supply chains in Taiwan. The results show that manufacturing is the niche in IoT industry. However, R&D exposed the shortcoming of IoT industry in Taiwan. The efficiencies of DMUs investing in the upstream as well as the middlestream outperforms in the IoT supply chains in Taiwan show best overall efficiencies. The case study verifies the usefulness of the proposed methods.

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