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Evaluating MTO Order Economic Performance for Parts Processing and Machining Production

Jason Z.-H. Lee
School of Management,
Marist College, Poughkeepsie, NY 12601, USA
E-mail: jason.lee@marist.edu

Angela H. L. Chen
Department of Industrial and Systems Engineering,
Chung Yuan Christian University, Taoyuan 320, Taiwan
E-mail: achen@cycu.edu.tw (*Corresponding Author*)

Che-An Wu
Department of Industrial and Systems Engineering,
Chung Yuan Christian University, Taoyuan 320, Taiwan
Email: g10974609@cycu.edu.tw

ABSTRACT

In a Taiwan metal parts processing company, orders often involve customization, tight deadlines, and small quantities, leading to additional costs that can distort profit assessment during quoting and production. This case study employs Data Envelopment Analysis (DEA) to assess how different types of make-to-order (MTO) orders impact costs and profits. Mass production type benefit from operational experience, enabling efficiency improvements. However, research and development (R&D) orders pose challenges due to unforeseeable factors like production failures and rework processes. We suggest classifying R&D orders based on complexity, customer requirements, and material types. Three key approaches for assessing order benefits include evaluating cost-effectiveness between in-house production and outsourcing, streamlining processes for efficiency, and integrating risk considerations into quotation accuracy and manufacturing cost analysis.

Keywords: *data envelope analysis, economic efficiency, make-to-order, order performance, order management.*

1. INTRODUCTION

In 2020, according to Taiwan's Ministry of Economic Affairs' 2021 Small and Medium-sized Enterprises (SMEs) White Paper, SMEs constituted 98.93% of enterprises, with sales surpassing half of the total. Manufacturers, comprising 9.34% of enterprises, saw sales accounting for 19.35%, with the "Metal Products Manufacturing Industry" contributing 12.08%. Despite COVID-19 downturns, the metal industry rebounded in Q4, growing 2.56%, driven by global economic stabilization, increased demand, and rising raw material prices. Consequently, the metal products manufacturing industry emerged as both the largest and a pivotal segment within Taiwan's manufacturing landscape which is dominated by SMEs adapting to trends. Orders now demand customization, featuring tight deadlines, small quantities, and diverse varieties and thus posing challenges in production management such as inventory and scheduling. Challenges such as order quotation/estimation and product process assessment often lead to profit miscalculation due to reliance on experiential rules, particularly with tight deadlines and diverse products.

More specifically, the above profit miscalculation can be attributed to two main factors. The technical side involves the failure to accurately estimate the manufacturing time required for the entire process, or the misjudgment of the company's own technical capabilities leading to extra costs. On the management side, there is the inability to effectively plan production schedules, or the negative impact on overall production operations due to urgent customer orders, indirectly affecting the utilization rate of the machines or resulting in increased expenses to add unnecessary costs. Therefore, production management lies in using experience or tools to lower the risk in production mistakes, enhance operational efficiency, and bring more profitability and benefits to the company.

This study focuses on order management, using a Taiwanese metal parts processing company (alias C company in the paper) for demonstration purposes. The scope is make-to-order (MTO) production and whether the benefits created by orders provide the company with sufficient surplus or lead to losses is assessed. Beforehand, an evaluation of engineering drawings and consideration of whether the production method has sufficient capacity are necessary. The existing scheduling within the factory also must be assessed for potential crowding-out effects and other related risks. Subsequently, order quotation/estimation is carried out, and then production if the order is accepted. For the products, each possessing uniqueness and mostly involving small-scale and diverse production, determining whether each batch of orders can generate sufficient profit becomes a key focus.

To achieve the goal of our study, Data Envelopment Analysis (DEA) is employed to evaluate how the order performance has been achieved and benchmarked. The analysis also explores how order types influence various costs and profits. Using the CCR (Charnes *et al*. 1978) model and BCC (Banker *et al*. 1984) model for empirical analysis, the study identifies orders with relatively low efficiency and their underlying reasons. Variable slack analysis is conducted to provide adjustment recommendations and managerial directions. Sensitivity analysis is also performed to investigate the critical variables affecting efficiency. Once issues and areas for improvement are summarized, they serve as useful feedback for managers to guide future adaptations.

2. RELATED STUDIES

The manufacturing industry encompasses both MTO and MTS (make-to-stock) systems (Günalay 2010). MTO systems are tailored to customer specifications, triggered by customer orders, while MTS systems rely on pre-made inventory for quick response to demand. MTO systems offer high customization, shorter delivery times, and reduced inventory. Although challenges faced by MTO include longer lead times and production scheduling issues due to customization, many organizations are shifting towards it completely (Zennaro *et al*. 2019) or partially, i.e., hybrid MTS-MTO (Rafiei & Rabbani 2009, Peeters & Van Ooijen 2020), considering increasing customer expectations for variety and customization.

Efficient production planning is crucial for timely order fulfillment in MTO environments. Various studies highlight the importance of order acceptance, machine control, and hierarchical production planning in MTO systems (e.g., Kerkkänen 2007, Okongwu *et al*. 2008, Wee *et al*. 2009, Hemmati 2012, Rafiei & Rabbani 2012, Li & Womer 2012, Rabbani *et al*. 2014, Fernandes *et al*. 2015, Rabbani & Dolatkhah 2017). Performance metrics such as total lead time, cycle time, and on-time delivery are essential for assessing the effectiveness of MTO systems, where challenges related to balancing lead times and inventory risks are often encountered (e.g., Sujan et al. 2012). Recent research in MTO includes supply chain risk management (Dohale *et al*. 2021), sequencing optimization (Martinelli et al. 2022), production time hedging (Zhai & Cheng 2021), and maintenance scheduling optimization (Qiu *et al*. 2021). Sustainable manufacturing practices (Upadhyay et al. 2023) are increasingly important for MTO producers such as automotive manufacturing.

While effective and efficient fulfillment and management process for MTO orders (e.g., order placement and processing, inventory management, shipping and delivery) is important, the aforementioned performance metrics for such efficiency and effectiveness and the resulting contributions to the business (e.g., profitability, customer satisfaction) from managing these orders both deserve inquiries. Once output and output variables associated with the order are defined, Data Envelopment Analysis (DEA) becomes an applicable approach for performance evaluation and/or benchmarking (Cook *et al*. 2014) if the order is considered as decision-making unit (DMU).

Numerous literature reviews delve into various aspects of the DEA method. For example, there are reviews that focus broadly on methodological developments and emerging research trends in DEA (Cook & Seiford 2009, Dyson *et al*. 2001, Emrouznejad *et al*. 2008, Emrouznejad & Yang 2018, Liu *et al*. 2016). Some other studies explore DEA's application in diverse fields like sustainability (Zhou *et al*. 2018), human development (Mariano *et al*. 2015), health (Pelone *et al*. 2015), banking and finance (Fethi & Pasiouras 2010), transportation (Cavaignac & Petiot 2017), insurance (Kaffash *et al*. 2020), and education (Johnes *et al*. 2017). These reviews play a crucial role in enhancing our understanding of how DEA is applied across different domains, offering guidance to both new and experienced researchers as they navigate DEA's complexities and potentials.

The rationale behind our study for evaluating order performance using DEA stems from the practice of using economic efficiency analysis for performance assessment. However, a gap exists in critically analyzing and synthesizing the knowledge accumulated over recent decades in this DEA application, as highlighted by Camanho *et al*. (2024). They note that while the analysis of economic efficiency using DEA originated with Färe *et al*. (1990), the focus has primarily been on cost efficiency, with revenue efficiency and profit efficiency remaining relatively understudied. Thus, Camanho *et al*.'s (2024) literature review specifically targets economic efficiency analysis using DEA, aiming to address this gap and enhance our understanding of DEA methodologies and applications in economic efficiency analysis.

3. RESEARCH METHODOLOGY

3.1 How: Research Methodologies Employed

“Company C” in Taiwan was used as a case study, where its business involves the processing of various parts, with clients spanning industries such as optoelectronics, semiconductor, automation, mold, and biomedical. The processed materials include aluminum alloy, titanium alloy, stainless steel, mold steel, tungsten steel, copper, and carbon steel. The processing operations are carried out based on customer-provided images. The data collection period for this study spans a year, from September 2018 to August 2019, during which order and quotation information from the company's clients is analyzed and discussed.

The business model is characterized by order-based production (or MTO), with two types of orders: mass production orders and research and development (R&D) orders (which are also called sample orders). Mass production orders are defined as those with quantities exceeding 6 units or with repeat orders from customers. R&D orders involve prototyping, using special materials, or processing based on specific specifications. We explored the production efficiency of received orders from different types of clients, considering the data of order characteristics (mass production and R&D) and inventory status for our analysis.

Three clients, I, II and III, were selected for our study’s purpose. Client I is a company in the optoelectronic products category, with both mass production and R&D orders. Their demand primarily involves mass production, with fewer custom and development orders. However, many R&D orders have the potential to become mass production items, requiring precision and high technical expertise and leading to relatively better profits. Client II is a semiconductor equipment supplier, mainly dealing with mass production orders. Their products are highly precise, and they cater to the increasing global demand for chips by expanding production capacity. Client III is a mechanical equipment factory, focusing on R&D orders to meet specific requirements. To the contrary, they take on customized orders, and the product specifications are diverse, with most being produced for the first time.

The data collected from these three clients involves a total of 18 orders, each being MTO based. In general, higher order quantities suggest stable products or larger demand, while lower order quantities may pertain to sampling or research and testing purposes.

3.2 Analysis Method

This DEA application focuses on economic efficiency analysis for MTO orders. It begins with selecting DMUs, where considerations must be made regarding their characteristics and constraints, as explained in four main aspects. Firstly, DEA can handle multiple input and output items simultaneously, avoiding the need to assume production functions or estimate parameters beforehand, thus ensuring accuracy. Secondly, the mathematical model generates weights determined by the DEA model, ensuring fairness as each evaluated unit is measured against the same criteria. Thirdly, DEA efficiency scores serve as comprehensive indicators, akin to Total Factor Productivity in Economics, offering insights into the usage status of evaluated units and providing directions for improvement. Fourthly, evaluation results represent relative efficiency rather than absolute efficiency, enabling comparisons among units to indicate better or worse performance.

Regarding constraints for selecting DMUs, two main aspects are elucidated. Firstly, the number of evaluation units should be at least twice the sum of output and input items, as per empirical rules. Secondly, input and output variables must be clearly defined and quantitative, without negative, zero, or extreme values, to prevent erroneous data impacting analysis results.

Our main DEA procedures, as outlined in **Figure 1**, involve several key steps. Firstly, the selection of DMUs requires homogeneity among evaluated units, ensuring similar goals, operations, or market environments. Homogeneity is maintained within the mechanical processing industry, assuming comparable factors influencing order profitability. To uphold homogeneity, the number of orders exceeds twice the sum of input and output items, while considering factors like product characteristics, production conditions, and market environment to address sample discreteness.

Secondly, in selecting input and output variables, the study aims to achieve a balanced assessment of both operational and financial efficiency. Organizational profitability indicators, such as order profitability, are incorporated, with isotonicity checked to ensure that output quantities do not decrease as input quantities increase. Correlation analysis is utilized to evaluate the alignment between activities and resources, aiding in the selection of appropriate input and output variables. The process of variable selection is further guided by insights from relevant literature, expert opinions, and the availability of data.

Subsequently, based on user objectives, input/output characteristics, and data types, suitable DEA analysis models are chosen, including efficiency/productivity and cross-year analysis (productivity indices). Scale and technical efficiency of DMUs are measured, commonly using CCR and BCC models. CCR model assesses total/overall efficiency, assuming Constant Returns to Scale (CRS), while BCC model evaluates pure technical efficiency, assuming Variable Returns to Scale (VRS), with scale efficiency (SE) obtained by dividing CCR by BCC results. Variable slack analysis and sensitivity analysis emphasize resource utilization among relatively inefficient units, discussing the effects of changing input/output variables and providing improvement suggestions.

3.3 Variable Selection and Description

Through our literature review, we identified key factors influencing the economic efficiency of company orders by linking this efficiency to the profits generated from the orders. Using data from completed orders at Company C, we analyzed the primary factors affecting the economic efficiency of each order. Order gross profit is derived by subtracting the cost of goods sold (COGS) from the order revenue. Further, the profit generated from the company's operations for completing an order—referred to as order operating income—is calculated by deducting the operating expenses related to the order from the order gross profit. The main factors directly impacting order efficiency are profits, revenue, and costs associated with each order, particularly manufacturing costs, which are imperative to consider when maximizing profits while minimizing costs.

Extended processing or idle time in Work in Process (WIP) can impose production management burdens and lower inventory turnover rates. Orders quantity affects operational efficiency, influencing scheduling, machine utilization, etc. Therefore, factors indirectly influencing efficiency include order completion days, manufacturing hours, and order quantity.

In summary, the study investigates the efficiency of resource utilization and scheduling arrangements within Company C. Based on the available data, we selected the following input variables: order completion days, material costs, internal costs, external costs, and manufacturing hours. These inputs represent the key resources required for manufacturing. For output variables, we included order quantity, order gross profit, and order operating income, which collectively represent the ultimate goals of the company's order fulfillment process. Specifically, we chose order quantity as an output variable to incorporate an operational perspective into the model, as it reflects the company's capacity to handle and process orders. This complements the inclusion of order gross profit and order operating income, which capture the financial dimension of performance. By structuring the model in this way, we aim to provide a balanced assessment of both operational and financial efficiency.

The variables we used in the analysis are listed and explained in **Table 1.** The data of 18 orders is shown in **Table 2.**

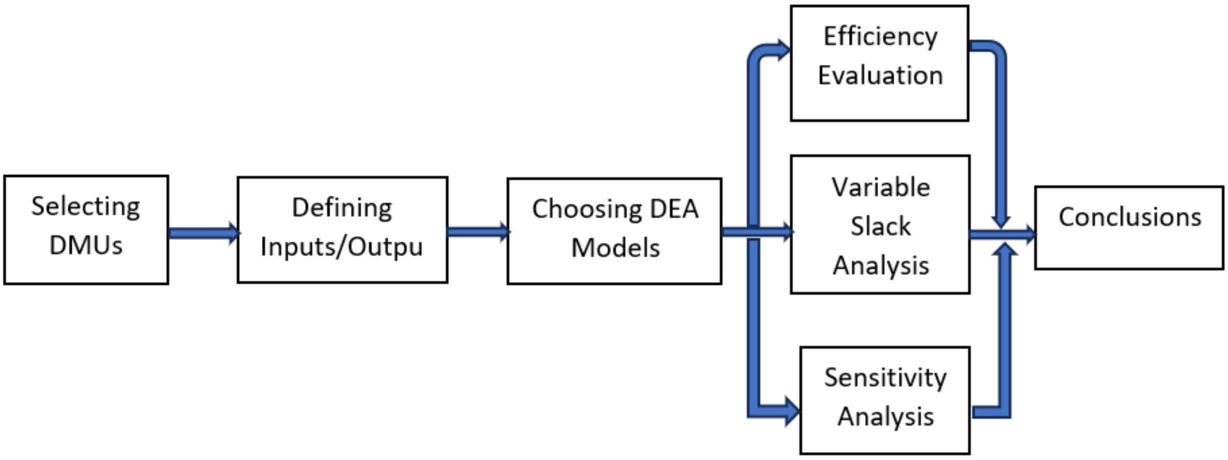

Figure 1 The process of using DEA for order efficiency assessment

Table 1 Descriptions of input and output variables associated with the order

	Variables	Description
Input	Order completion days	The time required from receiving the order to packaging and shipping out
	Material costs	Costs involving materials needed for production
	Internal costs	In-house production costs (e.g., labor, machine operation, quality control)
	External costs	Production cost of outsourcing
	Manufacturing hours	The time spent in the in-house manufacturing process
Output	Order quantity	The quantity of products or services requested by the customer in an order
	Order gross profit	The revenue generated from the transaction of the order (after applying applicable discounts to the transaction price) minus the cost of goods sold (COGS) directly associated with fulfilling that order
	Order operationg income	The order gross profit minus the operating expenses related to completing the order

Table 2 The data of variables associated with the 18 orders

DMU (Order)	Order completion days	Material costs	Internal costs	External costs	Manufacturing hours	Order quantity	Order gross profit	Order operationg income
A	19	$ 1,200	$ 60	$ 45	0	5	$ 6,000	$ 5,955
B	9	975	300	600	0	2	30,000	29,025
C	94	2,438	13,384	12,250	28.6	72	110,400	83,400
D	16	272	5,000	400	10	20	20,000	14,728
E	40	900	1,210	4455	2.5	4	9,000	3,395
F	48	8,080	404	17,740	0	120	40,400	22,660
G	4	440	1,375	440	5.5	44	22,000	20,625
H	8	100	7,000	680	17.5	40	34,000	26,900
I	9	4,800	240	480	0	8	24,000	24,000
J	9	4,200	210	189	0	14	21,000	20,811
K	4	440	1,375	440	5.5	44	22,000	20,625
L	6	77	3,250	77	6.5	4	3,832	582
M	7	250	1,400	46	2.5	1	2,300	650
N	7	160	600	160	1	2	8,000	7,400
O	62	1,690	7,500	348	15	24	17,400	8,370
P	17	22,500	4,000	2,250	16	90	112,500	108,500
Q	5	2,880	15,500	1,215	32	60	144,000	127,285
R	1	25	12.5	25	0	1	1,250	1,250
Max.	94	$ 22500	$ 15500	$ 17740	32.0	120	$144000	$127285
Min.	1	25	12.5	25	0.0	1	1250	582
Mean	20.27	2857.03	3490.03	2324.42	7.92	30.83	34893.4	29231.2
Std. Dev	24.25	5196.95	4502.30	4688.61	9.76	34.11	40989.8	36423.0

Note: A DMU represents an order, and the profits and costs associated with the order are presented in TWD (Taiwanese dollars).

4. ANALYSIS RESULTS AND IMPLICATIONS

Following the steps indicated in **Figure 1** with the DEA models selected, we proceeded with recommended analyses and the findings are summarized as follows.

4.1 Preliminary Observations

The significant differences between maximum and minimum values for each input variable (see Table 2) indicate distinct characteristics among order types (details in the original raw data). For example, the maximum manufacturing time is 32 hours (Order Q). The minimum is 0 (Orders A, B, F, I, J, R), where Order Q involves a mix of in-house and external production. Full outsourcing is used for Orders A, B, F, I, J, and R. This illustrates the difference in production capacity allocation.

Compared to Order R, a fully outsourced order that involves rework or custom-designed products and a single process of electroplating resulting in short production time, Order C requires four processes (cutting, grinding, surface treatment, heat treatment) with a total manufacturing time of 28.6 hours. Order C's 94 completion days from order to delivery vs. the minimum completion day of 1 among orders for Order R suggest a prolonged waiting and outsourcing period.

In addition, Order R's order quantity, material costs, and internal and external costs (1, $25, $12.5 and $25, respectively) are all the lowest among orders. The influence of order quantity, process complexity and precision requirements on costs can be showcased by comparing Orders P and Q with Order R. Order P has the highest material cost of $22,500 with an order quantity of 90. Order Q has the highest internal costs of $15,500, involving a high precision grinding process due to intricate equipment and technology requirements. As an outsourced order like R, Order F however has the greatest external costs ($17,740). This is because Order F involves external manufacturing with CNC lathe processes and thus incurs higher costs due to high precision specifications or intricate production difficulties.

4.2 Correlation Analysis

Table 3 shows that all correlation coefficients between input and output variables from the data of collected orders are positive (i.e., consistent with proportional expansion), ranging between 0.027 and 0.989. However, high correlations are observed between certain output variables while low correlations between certain input variables.

More specifically, with the highest being a coefficient of 0.989 between the order's gross profit and operating income, a proportional increase obviously exists in their relationship. Manufacturing hours and internal costs have the second-highest correlation (0.978), implying increased internal costs likely are associated with longer production times (e.g., longer hours of labor and machine operations). The third-highest correlation (0.826) is between order gross profit and manufacturing hours, suggesting intricate manufacturing processes potentially lead to better gross profit. This can be understood because in this case, the process risks are usually considered during pricing, leading to an increase in order revenue (and in turn gross profit and operating income). For example, Order Q has higher gross profit ($144,000) and operating income ($127,285) than any other orders. As mentioned earlier, this order involves intricate production processes, as evidenced by the prolonged manufacturing time of 32 hours.

The lowest correlation (0.027) is between internal costs and material costs. Market prices fluctuate for raw materials, constituting a predetermined expenditure rather than being influenced by internal costs. Hence, there is little direct (or linear) correlation above. The second lowest (0.104) is between material costs and completion days, showing that the complete manufacturing cycle covers pre-arrangements (e.g., product production, quality assurance inspections, packaging, shipping) with a less direct impact on the amount spent on raw material procurement. Correlation coefficients of 0.160 (manufacturing hours and external costs) and 0.167 (manufacturing hours and material costs) reveal the limited association of internal operational arrangements with costs with outsiders, such as material suppliers and collaborative businesses for outsourcing.

4.3 Overall Efficiency Evaluation

Each order is a DMU to be analyzed by using DEA-Solver 4.1 software. Initially, under a CCR model, overall efficiency scores (between 0 and 1) were calculated (see **Table 4**). A score of 1 indicates the order was generating the maximum benefit among 18 orders (i.e., relatively efficient). Otherwise, it did not (i.e., relatively inefficient). Thus, Orders A, B, F, G, H, I, J, K, P, Q, and R, totaling 11 orders, achieve relative efficiency. Among the 7 orders (C, D, E, L, M, N, O) with relative inefficiency, Order E has the lowest overall efficiency score (0.187). In the following analysis of order performance, we look into Order E as an illustrative example.

The examination of Order E is based on three perspectives: earnings, order production cycle, and management of in-house production and outsourcing. The reason is orders with profits exceeding 50% showcase accurate initial cost estimations, often associated with reproduction or simpler non-research items. In terms of production cycle efficiency, lower scheduling and production time costs are observed for orders with lower quantities and completion days. Concerning in-house and collaborative factory management, diverse product designs and in-house capacity configurations impact cost distribution in production processes. Proper scheduling and cost estimation for each order can enhance overall efficiency indirectly.

Order E consists of four items, each with very low demand (sometimes just 1 unit). These items are typically associated with new product(s), having more completion days and a lower machine utilization rate. This leads to a higher delivery time cost and in turn affects earnings. In addition, the core manufacturing processes for Order E are outsourced to a collaborative factory. Considering the production cycle, the complexity and precision requirements of these processes result in external costs accounting for 60% of the total cost (see **Table 2**). Thus, the external costs warrant closer attention for improvement.

Table 3 The data of variables associated with the 18 orders

	Order completion days	Material costs	Internal costs	External costs	Manufacturing hours	Order quantity	Order gross profit	Order operating income
Order completion days	1							
Material costs	0.104	1						
Internal costs	0.432	0.027	1					
External costs	0.698	0.266	0.183	1				
Manufactuiring hours	0.390	0.167	0.978	0.160	1			
Order quantity	0.401	0.613	0.388	0.731	0.468	1		
Order gross profit	0.296	0.536	0.772	0.338	0.826	0.674	1	
Order operating income	0.179	0.579	0.714	0.226	0.784	0.621	0.989	1

Table 4 Evaluation of order efficiencies

DMU	Overall efficiency score (CCR)	Pure technical efficiency score (BCC)	Scale efficiency (SE) score	Returns to scale
A	1.000	1.000	1.000	Constant
B	1.000	1.000	1.000	Constant
C	0.670	1.000	0.670	Decreasing
D	0.796	0.809	0.984	Constant
E	0.187	0.264	0.708	Decreasing
F	1.000	1.000	1.000	Constant
G	1.000	1.000	1.000	Constant
H	1.000	1.000	1.000	Constant
I	1.000	1.000	1.000	Constant
J	1.000	1.000	1.000	Constant
K	1.000	1.000	1.000	Constant
L	0.742	0.840	0.883	Constant
M	0.415	0.684	0.607	Constant
N	0.888	1.000	0.888	Decreasing
O	0.718	0.735	0.977	Constant
P	1.000	1.000	1.000	Constant
Q	1.000	1.000	1.000	Constant
R	1.000	1.000	1.000	Constant
Mean	0.856	0.907	0.929	

From the perspective of management of in-house vs. outsourcing, the extended production time and outsourcing costs of Order E impact earnings and overall efficiency. The initial profit estimation and actual production-related costs do not align, partly due to a long waiting time for scheduling when outsourcing to collaborative manufacturers. Since the order involves R&D products, unfamiliarity with the production method results in a longer development and process design. This uncertainty leads to longer production time and higher outsourcing cost, negatively impacting overall efficiency.

In short, from the stage of receiving R&D order(s), it is advisable to conduct an internal capacity assessment within the company. This involves evaluating the ability to internally manufacture and determining whether existing scheduling practices lead to congestion effects. Adjustments should be made to the costs associated with in-house production and collaboration with external factories to align with economic efficiency. When providing quotations, it is recommended to incorporate relevant risks into the assessment. These steps contribute to enhancing the overall efficiency of the order.

4.4 Pure Technical Efficiency Evaluation

Pure technical efficiency scores were obtained using the BCC model to investigate whether resource allocation is effectively utilized and appropriately distributed. As shown in **Table 4**, 13 orders, A, B, C, F, G, H, I, J, K, N, P, Q, and R, have a pure technical efficiency score of 1, suggesting well-optimized production capacity or coordinated production scheduling for these orders. However, Orders C and N have overall efficiency scores of 0.670 and 0.888, respectively. This implies that although their resource allocation (e.g., production arrangements, timely scheduling, profit estimation) is effective, the lack of a proportional increase in input and output quantities hinders achieving a SE of 1. There is room for improvement in input quantities.

5 orders with a pure technical efficiency score less than 1, ranked from highest to lowest, are L, D, O, M, and E, indicating inefficient use of resources. Order E's pure technical efficiency score is not just the lowest but also considerably lower than L, D, O, M. This can be understood by the aforementioned nature of Order E, being related to the production of new products, and thus unfamiliarity with the production process, and complex procedures lead to higher external costs and longer production days. It is suggested that managers, upon receiving orders involving new product development, evaluate various aspects such as in-house and outsourced process capabilities and associated costs. This comprehensive assessment can help optimize the use of existing resources and enhance the pure technical efficiency.

4.5 Scale Efficiency (SE) Evaluation

SE assesses how well a particular DMU is operating in terms of its scale of production or operation. Here it highlights the order's performance in terms of Constant Returns to Scale (CRS), Increasing Returns to Scale (IRS), or Decreasing Returns to Scale (DRS), meaning whether the operations for the order have been at its optimal scale, underutilizing its resources, or beyond its optimal scale.

Table 4 shows that the average SE score is 0.929, indicating a room of 0.071 for improvement to the optimal SE. Orders with a SE score above the average are A, B, D, F, G, H, I, J, K, O, P, Q, and R, totaling 13 orders, reflecting a proportional change in outputs concerning various input costs, order completion time, order quantity, and profit expenses. However, orders with SE below the average are C, E, L, M, N, totaling 5 orders, indicating that resource input and output do not increase proportionally. It is suggested to consider adjustments of costs, working hours, and/or completion days for the orders by learning about their situation of returns to scale, CRS, IRS or DRS, to enhance SE.

For instance, when SE shows DRS, as seen in Orders C, E, N with SE scores of 0.670, 0.708, 0.888, it suggests inefficient resource use and excessive resource input. Recommendations include adjusting input resources, such as reducing manual labor and machinery-heavy tasks, refining processes to improve yield, and developing multiple subcontractors to optimize the supply chain, reducing costs and delivery times, thus improving SE.

For orders with a SE score higher than the pure technical efficiency score, indicating CRS, such as D, L, O with SE scores of 0.984, 0.883, it implies high internal costs (due to its use of grinding machine). These orders have higher manufacturing costs but relatively lower profits due to complex equipment and technical requirements. It is recommended to readjust relevant costs according to the manufacturing process during order evaluation to increase profitability.

It is appropriate to point out the situation that three efficiency scores (overall, technical and scale) of an order all show a low mark. Order M is one example. This order has the status of CRS, meaning the order's resource scale is optimal, with inputs and outputs in proportion. However, internal cost resource utilization is not efficient, resulting in an Operating Efficiency Ratio (OER) of ~ 28%. It is suggested to improve the manufacturing process to reduce costs and increase the quoted amount to enhance profitability. For future similar orders, the management may want to consider whether to accept the requirements of the order or renegotiate, while evaluating order efficiency.

4.6 Order Characteristics vs Efficiency

To investigates how different order characteristics can affect a company's profitability performance, orders are categorized into two types: mass production and R&D (or sample orders). Overall efficiency analysis is then conducted separately for each type.

The 18 orders (referred to as the group of mixed orders) are categorized by order quantity. Those with 6 or more are mass production orders (C, D, F, G, H, I, J, K, P, Q), and the rest are R&D orders. Subsequently, efficiency analysis is performed for these two groups separately, and the efficiency scores are presented in **Table 5.**

Within the group of 10 mass production orders, 8 orders appear to be overall efficient and 2 (C and D) are not. These 8 orders carry the overall efficiency score of 1 from **Table 4** (where all 18 orders are compared) to **Table 5** (where mass production orders are compared). This indicates that the characteristics of these orders are not the significant factor affecting their performance; instead, their efficiency likely is attributed to their better planning and configuration overall. Concerning Orders C and D, both achieve technical efficiency. However, the former may allocate excessive resources, while the latter requires additional resource input to improve overall efficiency (as indicated in their calculated "returns to scale").

As shown in **Table 5**, there are a total of 8 R&D orders among which Orders L, N, O, and R are considered more efficient overall, while the rest (A, B, E, M) have an overall efficiency score less than 1. Note that the overall efficiency scores of Orders L, N, O in **Table 4** are 0.742, 0.888, and 0.718, respectively. That is, the resource utilization of these 3 orders is considered efficient when just compared with their own kind. Order R's efficiency is attributed to its better planning and configuration overall, less pertaining to its characteristics (R&D or mass production).

With the examination of pure technical and SE scores for the R&D orders considered inefficient overall, Orders A's and B's scale efficiencies show that their resource inputs do not yield proportional outputs. On the other hand, the technical efficiencies of Orders E and M indicate inefficient resource allocation.

4.7 Reference Group Analysis

The frequencies of being used as a reference for each order with an overall efficiency of 1 are shown in **Table 6**, where the 18 orders, mass production and R&D, are all included while assessing order (relative) efficiency.

With a relative efficiency score of 1, the order serves as a reference for those with relative inefficiency. The orders used as references for an inefficient order comprise a reference group set. The higher the frequency of an order being used as a reference, the more reliable this order's overall efficiency score, making it a better reference for resource allocation and scale adjustment for those relatively inefficient. On the other hand, the orders in the reference group are those with similar production methods or models to the relatively inefficient ones. For example, Order C’s reference group includes H, Q, and R, indicating that these three orders can serve as references for resource allocation and production mode improvement for C to enhance overall efficiency.

It appears that a higher frequency of being a reference is associated the order involving products having sufficient inventory, higher order quantities, or better profitability. For example, Orders G, H, and Q have order quantities exceeding 6, belonging to mass production orders, and have an OER reaching over 70%. Also, except for Order H, G and Q have carried inventory. For Orders A and R, the order quantities are 5 and 1, respectively. Although being a R&D order, they have the OER reaching 90% and good inventory. The above observation indicates that the factors of order quantity, inventory level, and profit will influence the selection of the reference group set.

Table 5 Efficiency evaluation for the groups of mass production and R&D orders separately

	DMU	Overall efficiency score (CCR)	Pure technical efficiency score (BCC)	Scale efficiency (SE) score	Returns to scale
Mass production	C	0.892	1.000	0.892	Decresing
	D	0.796	1.000	0.796	Increasing
	F	1.000	1.000	1.000	Constant
	G	1.000	1.000	1.000	Constant
	H	1.000	1.000	1.000	Constant
	I	1.000	1.000	1.000	Constant
	J	1.000	1.000	1.000	Constant
	K	1.000	1.000	1.000	Constant
	P	1.000	1.000	1.000	Constant
	Q	1.000	1.000	1.000	Constant
	Mean	0.969	0.907	0.969	
R&D	A	1.000	1.000	0.892	Constant
	B	1.000	1.000	0.796	Constant
	E	0.200	0.627	1.000	Decreasing
	L	1.000	1.000	1.000	Constant
	M	0.776	0.776	1.000	Constant
	N	1.000	1.000	1.000	Constant
	O	1.000	1.000	1.000	Constant
	R	1.000	1.000	1.000	Constant
	Mean	0.872	0.925	0.961	

Table 6 Reference group sets for relatively inefficient orders

DMU	Overall frequency score	Reference group set	Frequency of being used as a reference
A	1.000	-	2
B	1.000	-	0
C	0.670	H、Q、R	0
D	0.796	G、H、Q	0
E	0.187	H、R	0
F	1.000	-	0
G	1.000	-	3
H	1.000	-	5
I	1.000	-	0
J	1.000	-	0
K	1.000	-	0
L	0.742	G、H、Q	0
M	0.415	A、Q	0
N	0.888	H、Q、R	0
O	0.718	A、G、Q	0
P	1.000	-	0
Q	1.000	-	6
R	1.000	-	3

4.8 Variable Slack Analysis

The CCR model assumes constant returns to scale and homogeneity of inputs and outputs, while the BCC model allows for a more flexible assessment of efficiency in the presence of variable returns to scale and heterogeneous inputs and outputs. Thus, the examination of inputs and outputs for variable slack analysis under the CCR model is considered for a long-term improvement goal, and such an examination under the BCC model offers insights into a short-term strategy.

To analyze input and output levels for units with efficiency scores less than 1, we employ variable slack analysis, comparing optimal and actual values for each variable. This method assesses resource utilization potential, identifying slack variables that can be improved to enhance efficiency. Negative slack values for inputs suggest excess resource usage, recommending resource reduction. Positive slack values for outputs indicate production, sales, or profit losses, suggesting adjustments such as setting minimum production levels or pricing modifications to improve efficiency.

Table 7 Variable slack values and adjustment magnitudes (in %) for each input and output in the CCR model

		Inputs					Outputs		
Order	**Overall efficiency**	**Order completion days**	**Material costs ($)**	**Internal costs ($)**	**External costs ($)**	**Manu-facturing hours**	**Order quantity**	**Order gross profit ($)**	**Order operating income ($)**
A	1.000	0	0	0	0	0	0	0	0
B	1.000	0	0	0	0	0	0	0	0
C	0.670	-31.012 (-32.99%)	-804.340 (-32.99%)	-4878.688 (-36.45%)	-10137.473 (-82.75%)	-9.436 (-32.99%)	25.830 (35.87%)	0	19010.725 (22.79%)
D	0.796	-12.825 (-80.15%)	-55.359 (-20.35%)	-1891.012 (-37.82%)	-81.411 (-20.35%)	-2.350 (-23.50%)	0	0	2071.990 (14.07%)
E	0.187	-33.192 (-82.98%)	-731.850 (-81.32%)	-983.931 (-81.32%)	-4275.000 (-95.96%)	-2.142 (-85.70%)	3.462 (86.54%)	0	5459.942 (160.82%)
F	1.000	0	0	0	0	0	0	0	0
G	1.000	0	0	0	0	0	0	0	0
H	1.000	0	0	0	0	0	0	0	0
I	1.000	0	0	0	0	0	0	0	0
J	1.000	0	0	0	0	0	0	0	0
K	1.000	0	0	0	0	0	0	0	0
L	0.742	-5.493 (-91.55%)	-19.783 (-25.81%)	-2766.994 (-85.14%)	-19.783 (-25.81%)	-5.283 (-81.27%)	0	0	2749.147 (472.36%)
M	0.415	-5.914 (-84.48%)	-146.168 (-58.47%)	-1183.801 (-84.56%)	-26.895 (-58.47%)	-2.060 (-82.41%)	0.092 (9.22%)	0	1417.909 (218.14%)
N	0.888	-2.384 (-34.06%)	-17.972 (-11.23%)	-161.865 (-26.98%)	-17.972 (-11.23%)	-0.112 (-11.23%)	4.201 (210.04%)	0	199.573 (2.70%)
O	0.718	-44.958 (-72.51%)	-476.006 (-28.17%)	-6517.204 (-86.90%)	-98.018 (-28.17%)	-11.944 (-79.63%)	0	0	8031.591 (95.96%)
P	1.000	0	0	0	0	0	0	0	0
Q	1.000	0	0	0	0	0	0	0	0
R	1.000	0	0	0	0	0	0	0	0
Total adjustment (Mean adj. mag.)		-135.778 (-26.60%)	-2251.478 (-126.28%)	-18383.495 (-24.40%)	-14656.552 (-17.93%)	-33.327 (-22.04%)	33.585 (18.98%)	0 (0.00%)	38940.877 (54.82%)

The analysis results in **Table 7** show 11 relatively efficient orders (A, B, F, G, H, I, J, K, P, Q, R), with a variable slack value of 0 for all inputs and outputs, indicating no need for adjustments. However, adjustments are needed for 7 orders (C, D, E, L, M, N, O) to achieve efficiency. Taking the order with the lowest overall efficiency, E, as an example, its efficiency score is 0.187. To enhance this efficiency, the completion time needs to be reduced by 33.192 days which is 82.98% less than the actual (i.e., adjustment % magnitude). Other recommended adjustments include material costs to be reduced by approximately $732 TWD (81.32%), internal costs to be reduced by about $984 TWD (81.32%), external costs to be reduced by $4,275 TWD (95.96%), and manufacturing hours to be reduced by 2.142 hours (85.70%). Regarding Order E's outputs, order quantity needs to be increased by approximately 4 units, representing an adjustment magnitude of 86.54% (i.e., 86.54% greater than the actual). Also, its operating income should be increased by about $5,460 TWD (160.82%).

For order E, the external costs and order operating income need the greatest adjustment % magnitude as input and output variables, respectively. Therefore, it is recommended that the company assess its internal production capacity, evaluate whether it has the capability to produce the required items, and analyze whether the existing scheduling has any crowding-out effects. Adjustments should also be made to the cost allocation between in-house production and outsourcing to achieve economic efficiency. Additionally, it is suggested that relevant risks be considered during the quotation process to enhance the overall efficiency of the order.

As mentioned earlier, the variable slack analysis in the CCR model pertains to long-term goals for overall efficiency improvement. It is recommended to analyze the applicability of each variable for orders that require improvement. A comprehensive view of the adjustment % magnitudes for the input variables indicates that material costs require the largest mean adjustment % magnitude of 126.28%, followed by 26.60% for order completion time. Among the output items, order operating income shows the largest adjustment % magnitude suggested (54.82%). This observation can be understood as follows.

Material costs need periodic evaluation and updating of estimation bases due to factors such as customer-supplied materials, modifications to original components, special material qualities, and market price fluctuations. In addition to considering various costs, schedules, transportation operations, packaging to shipment, and ensuring that the completion time of each order meets customer requirements, it is essential to reduce idle materials and avoid the accumulation of unfinished products in the warehouse. This prevents burdens on production management and ensures a higher turnover rate of funds. Moreover, the management should evaluate whether the cost and risk assessments for each order are appropriate to ensure satisfactory profitability.

The analysis results of the BCC model are presented in **Table 8**. 13 orders are relatively efficient (A, B, C, F, G, H, I, J, K, N, P, Q, R) with a variable slack value of 0 for all inputs and outputs, indicating no need for adjustments. Adjustments are needed for 5 orders (D, E, L, M, O) to achieve efficiency. Taking the order with the lowest pure technical efficiency, E, as an example, its pure technical efficiency score is 0.264. To enhance this efficiency, the completion time needs to be reduced by 35.824 hours, meaning the adjustment magnitude of 89.05%. Other adjustments include material to be reduced by approximately $6 TWD (73.63%), internal costs to be reduced by about $891 TWD (73.63%), external costs to be reduced by $4,275 TWD (95.96%), manufacturing hours to be reduced by 1.841 hours (73.63%). Also, order quantity needs to be increased by approximately 1 unit (7.83%), and order operating income needs to be increased by about $5,189 TWD (152.84%).

Order E's external costs and order operating income on the input and output sides, respectively, are recommended for the highest adjustment %. So, when the company has the capability to produce internally, it is recommended to reassess whether the time and related costs are beneficial. Considerations for the special nature of the materials used and whether they are suitable for internal production are also important. On the other hand, this order involves R&D components with a low quantity. The potential for a shift from R&D to mass production for the long run deserves the management's attention to increase its order operating income as suggested by the analysis.

For short-term improvement goals, **Table 8** presents the results of the BCC model's calculation of adjustment magnitudes for each variable. Among input variables, the recommended mean adjustment % of internal costs is the highest at 21.39%, followed by the completion time's 21.25%. Among the output items, order operating income shows the largest adjustment % magnitude suggested (56.10%). With the above finding, the management might want to reassess whether it is more cost-effective to outsource the production of products to external suppliers. When both in-house and external productions have sufficient capacity, how to arrange them effectively should be evaluated.

Similar to the earlier advice from the CCR model, in addition to considering various costs, schedules, transportation operations, packaging to shipment, and whether the completion time of each order meets customer requirements, it is essential to reduce idle materials and avoid the accumulation of unfinished products in the warehouse. This prevents burdens on production management and ensures a higher turnover rate of funds. It is recommended to assess whether the cost and risk for each order are appropriate to ensure profitability meeting the business goal.

4.9 Sensitivity Analysis

To investigate the impact of an individual variable (input or output) on order efficiency, sensitivity analysis is performed by removing the variable and then recalculating the efficiency of the order. The purpose is to highlight the influence of each variable on order efficiency when the manager considers changes to specific input(s) or seeks improvement for certain output(s). The analysis results are presented in **Table 9**.

Taking the removal of material costs in the CCR model as an example, the overall efficiency scores for Orders C, D, E, H, L, M, N, and O decreased from 0.670 to 0.302 (change = -0.368), 0.796 to 0.582, 0.187 to 0.083, 1.000 to 0.690, 0.742 to 0.577, 0.415 to 0.404, 0.888 to 0.442, and 0.718 to 0.660, respectively. No efficiency change was observed for the other orders. This results in a mean efficiency change of -0.093 for the 18 orders. The above observation indicates that these 8 orders are more susceptible to changes in material costs. This information can guide management in developing order-specific improvement strategies for enhancing order performance.

Table 8 Variable slack values and adjustment magnitudes (in %) for each input and output in the BCC model

		Inputs					Outputs		
Order	Pure technical efficiency	Order completion days	Material costs ($)	Internal costs ($)	External costs ($)	Manu-facturing hours	Order quantity	Order gross profit ($)	Order operating income ($)
A	1.000	0	0	0	0	0	0	0	0
B	1.000	0	0	0	0	0	0	0	0
C	1.000	0	0	0	0	0	0	0	0
D	0.809	-12.351 (-77.20%)	-52.077 (-19.15%)	-1973.305 (-39.47%)	-76.583 (-19.15%)	-2.560 (-25.60%)	0	0	2165.202 (14.70%)
E	0.264	-35.824 (-89.05%)	-662.701 (-73.63%)	-890.965 (-73.63%)	-4275 (-95.96%)	-1.841 (-73.63%)	0.313 (7.83%)	0	5188.929 (152.84%)
F	1.000	0	0	0	0	0	0	0	0
G	1.000	0	0	0	0	0	0	0	0
H	1.000	0	0	0	0	0	0	0	0
I	1.000	0	0	0	0	0	0	0	0
J	1.000	0	0	0	0	0	0	0	0
K	1.000	0	0	0	0	0	0	0	0
L	0.840	-4.701 (-78.35%)	-12.243 (-15.97%)	-2920.900 (-89.87%)	-12.243 (-15.97%)	-5.672 (-87.27%)	0	0	2921.493 (501.97%)
M	0.684	-3.901 (-55.73%)	-78.897 (-31.56%)	-1327.773 (-94.84%)	-14.517 (-31.56%)	-2.388 (-95.52%)	0.670 (66.99%)	0	1586.265 (244.04%)
N	1.000	0	0	0	0	0	0	0	0
O	0.735	-50.897 (-82.09%)	-447.897 (-26.50%)	-6541.805 (-87.22%)	-92.230 (-26.50%)	-11.973 (-79.82%)	0	0	8056.109 (96.25%)
P	1.000	0	0	0	0	0	0	0	0
Q	1.000	0	0	0	0	0	0	0	0
R	1.000	0	0	0	0	0	0	0	0
Total adjustment (Mean adj. mag.)		-107.674 (-21.25%)	-1253.815 (-9.27%)	-13654.748 (-21.39%)	-4470.573 (-10.51%)	-24.434 (-20.10%)	0.983 (4.16%)	0 (0.00%)	19917.998 (56.10%)

Considering the CCR and BCC models together, Orders A, B, F, G, J, K, Q, and R initially had an efficiency score of 1, and their efficiencies remain after removing an input or output variable. This indicates that these 8 orders have good planning in various output and input aspects, ensuring good order benefits regardless of long-term or short-term strategies. Note that Order P maintained a technical efficiency score of 1 (not overall efficiency) whichever variable is removed, indicating that its planning is suitable for short-term strategies and the order retains its efficiency regardless of the variations in individual variables.

For the CCR model, material costs, external costs, and order gross profit appear to be the top three influential variables (with a greater magnitude of mean efficiency change) for order overall efficiency. These influential variables are also the top three for order pure technical efficiency in the BCC model. Material costs have the most significant impact on order efficiency and thus management should focus on optimizing and reducing material costs not only for the near future, but also in the long run. Also, management can consider optimizing external costs and evaluating the balance between in-house production and external collaboration. For example, developing and cultivating more suppliers can enhance the supply chain, offering strategic advantages. The observed impact of order gross profit highlights the importance of evaluating the cost and risk assessments for each order to ensure profitability aligns with business goals. This insight underscores the need for robust risk management and assessment practices in the decision-making process. On the other hand, market fluctuations affecting raw material prices should be incorporated into the company's pricing strategy based on current market conditions. This adaptive approach can help maintain pricing accuracy and responsiveness to market changes.

In summary, the managerial insights derived from the analysis results include specific recommendations for cost reduction, order-specific strategies, considerations for long-term and short-term planning, optimization of external costs and supply chain management, and the importance of adapting to market fluctuations. These insights can guide decision-making and strategic planning for improved overall efficiency and business performance.

Table 9 Sensitivity analysis results

Original (CCR model)		Recalculated CCR's efficiencies after the variable is removed							
Order	Overall efficiency	Order completion days	Material costs	Internal costs	External costs	Manu-facturing hours	Order quantity	Order gross profit	Order operating income
A	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
B	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
C	0.670	0.652	0.302	0.670	0.670	0.653	0.670	0.546	0.670
D	0.796	0.796	0.582	0.796	0.663	0.796	0.763	0.730	0.796
E	0.187	0.187	0.083	0.183	0.187	0.187	0.187	0.083	0.187
F	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
G	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
H	1.000	1.000	0.690	1.000	1.000	1.000	1.000	1.000	1.000
I	1.000	1.000	1.000	0.970	1.000	1.000	1.000	1.000	1.000
J	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
K	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
L	0.742	0.742	0.577	0.742	0.262	0.742	0.655	0.522	0.742
M	0.415	0.415	0.404	0.415	0.153	0.415	0.415	0.219	0.415
N	0.888	0.888	0.442	0.888	0.828	0.863	0.888	0.864	0.888
O	0.718	0.718	0.660	0.718	0.1889	0.718	0.417	0.678	0.718
P	1.000	0.595	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Q	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
R	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Mean efficiency change		-0.024	-0.093	-0.002	-0.081	-0.002	-0.023	-0.043	0.000

Original (BCC model)		Recalculated BCC's efficiencies after the variable is removed							
Order	Pure technical efficiency	Order completion days	Material costs	Internal costs	External costs	Manu-facturing hours	Order quant ity	Order gross profit	Order operating income
A	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
B	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
C	1.000	1.000	0.543	1.000	1.000	1.000	0.889	1.000	1.000
D	0.809	0.809	0.584	0.809	0.746	0.809	0.768	0.739	0.809
E	0.264	0.264	0.088	0.262	0.264	0.255	0.264	0.127	0.264
F	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
G	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
H	1.000	1.000	0.692	1.000	1.000	1.000	1.000	1.000	1.000
I	1.000	1.000	1.000	0.971	1.000	1.000	1.000	1.000	1.000
J	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
K	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
L	0.840	0.840	0.696	0.840	0.403	0.840	0.763	0.704	0.840
M	0.684	0.684	0.650	0.684	0.157	0.684	0.684	0.543	0.684
N	1.000	1.000	0.502	1.000	1.000	0.943	1.000	1.000	1.000
O	0.735	0.735	0.731	0.735	0.223	0.735	0.438	0.682	0.735
P	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Q	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
R	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Mean efficiency change		0.000	-0.103	-0.002	-0.086	-0.004	-0.029	-0.030	0.000

5. CONCLUDING REMARKS

Our study focuses on economic efficiency, incorporating economic variables. Our DEA application may be framed more as benchmarking than straightforward production process analysis, aligning with Cook *et al*.'s observation (2014) that inputs are of the 'less-the-better' type and outputs are of the 'more-the-better' type. This distinction implies a multiple-criteria evaluation methodology treating DMUs as alternatives. In this context, DEA inputs and outputs represent two sets of performance criteria: one set to be minimized and the other to be maximized. Given the constraints of the available company data, we calculated efficiency scores using DEA and sought to explain these scores from managerial perspectives. This explanation is based on qualitative insights gained from managers regarding order characteristics and fulfillment processes (e.g., price quotation, subcontracting, in-house production, and resource management). Additional data, particularly on these qualitative aspects, would have enabled further exploration of determinant variables influencing efficiency scores, such as through Tobit model analysis. Nevertheless, we believe our work highlights the potential of DEA as a valuable tool in order management, offering insights into how it can enhance performance measurement and benchmarking in real-life non-production contexts (Wojcik et al. 2019).

After conducting the DEA method to evaluate overall efficiency, pure technical efficiency, and SE, this study proposes three key directions for improvement. Firstly, a thorough assessment of the cost-effectiveness difference between in-house production and outsourcing to collaborative manufacturers is recommended. Secondly, streamlining operational processes or modularizing to enhance efficiency and reduce costs is suggested. Thirdly, during order assessments, considering relevant risks to improve quotation accuracy and integrating relevant operations into the manufacturing cost analysis system is advised. Establishing such a system as a database concept would facilitate ongoing adjustments and enhance order estimation accuracy, reducing risks for future business undertakings.

Our study, focused on a single machining factory, suggests future research should include other similar case companies for a more comprehensive analysis. This approach allows for diverse comparisons of order efficiency and the consideration of influential factors such as product design costs, mold fees, achievement rates, complaint rates, and other variables. These findings not only make order estimation more beneficial but also increase competitiveness between companies and promote mutual learning.

Orders are categorized into mass production and R&D (or sample) types for a more in-depth understanding of efficiency differences. The reasons for classification, including factors like the complexity of production methods, urgency of orders, precision requirements for product specifications, and material properties, can be used as a database for future order estimation planning and cost adjustments.

In conclusion, the study recommends ongoing adjustments based on the Malquist Productivity Index (MALMQUIST) model analysis to assess inter-temporal efficiency changes. A positive trend in efficiency growth suggests effective adjustments and improvements, while a negative trend may indicate a deviation from proposed recommendations or external environmental influences. The establishment of a cost analysis system, informed by overall efficiency analysis and adjusted directions, serves as a valuable tool for future business decisions and managerial insights, contributing to the continuous improvement of operational efficiency.

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Jason Z.-H. Lee is an Associate Professor of Operations and Management Science at Marist College. His recent research interests include applied operations research, economic and decision models, and optimization.

Angela H. L. Chen is an Associate Professor of Operations and Logistics Management at Chuang Yuan Christian University, Taiwan. Her research focuses on resource planning in project management, data analytics in public transportation, and omnichannel site selection and performance. Her recent research projects received funding from the National Science Council and Ministry of Science and Technology of Taiwan, and the results have led to publications in reputable journals such as Public Transport and Applied Sciences. She is also a member of the Chinese Institute of Industrial Engineers and the Institute of Industrial Engineers (I.I.E.).

Che-An Wu earned a Master's degree in Industrial and Systems Engineering from Chuang Yuan Christian University, Taiwan, in 2021. Her research aimed to optimize efficiency and performance in manufacturing settings by evaluating various types of MTO (Make-to-Order) orders for parts processing and machining production. Currently, she works as a Project Procurement Specialist at the National Chung-Shan Institute of Science and Technology (NCSIST), where she procures and manages resources for critical projects.