CHIEN-MING CHEN

Evaluation and Design of Supply Chain Operations Using DEA

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Evaluatie en ontwerp van supply chain operaties gebruik makend van DEA

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Chien-Ming Chen
Los Angeles, the USA
April 2009

Contents

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Introduction to the thesis

"Without changing our pattern of thought, we will not be able to solve the problems we created with our current pattern of thought." Albert Einstein

The primary purpose of this thesis is to develop new approaches to address some important issues concerning the evaluation and design of supply chain operations. We focus on two main topics: evaluation of operational performance of processes with a interrelated internal structure (e.g., operations in a supply chain) in a dynamic setting, and system design under risks and uncertainty. Specific definitions of the problems will be introduced later in this chapter.

Our methodologies are developed mainly based on the Data Envelopment Analysis (DEA) approach. DEA is a mathematical programming approach to evaluating the efficiency of homogeneous production units. As a performance measure, DEA has an attractive feature that its score can account for multiple resources used and multiple outputs created in business operations. The output of DEA is a composite score that indicates a firm's relative efficiency as compared with its peer firms. Consequently, DEA has gained widespread popularity because of its simplicity in interpretation and calculation. The theory of DEA is built on a few general assumptions on the production model, which make it applicable to a variety of evaluation problems. This advantage does not imply that DEA is frail in its theoretical foundation. DEA not only has a strong connection with production economics, but also well-defined statistical properties that have been extensively discussed in the literature. Traditional DEA models, however, are not applicable to our problems—they are appropriate only for individual and time-independent production processes, and cannot deal with problems containing uncertain variables. In this thesis, we make theoretical and applied extensions to the former DEA models, and develop integrated methodologies that combine DEA with simulation and statistic techniques.

We begin this chapter by a background discussion of supply chain operations. Subsequently we will delineate current issues regarding the evaluation and design of operations.

1.1 Supply chain operations and evaluation

Over the years we have witnessed the growing importance of supply chain operations and supply chain management (SCM), as supply chains play a major role in every step of the product life cycle. Following the prevalence of SCM practices, the competitiveness of a firm will depend on the firm's ability to integrate its complex network of business relationships (Lambert and Cooper, 2000; Vickery et al, 1999)—a firm's performance will depend on that of its upstream and downstream partners in the supply chain, and simultaneously the performance of a supply chain will be determined by the joint success of supply chain members.

Many firms have actively engaged in supply chain initiatives, and have achieved superior operational and financial performance (Hausman, 2005). The well-known examples include Wal-Mart's cross-docking strategy, Dell's direct-sell business model, Hewlett-Packard's late differentiation strategy, and the POS (point of sale) system to receive early demand signals (e.g., Lee et al, 2004a). More recently, increased stakeholder pressure and tighten regulations have brought the environmental performance of firms under the spotlight. Company executives are now expected to incorporate the concept of green supply chains into every business process, and to discover opportunities to reduce the environmental impact of their products. As supply chains encompass all stages of product life cycles—from sourcing, manufacturing, delivery, to the recycling of end-of-life products, plenty opportunities and challenges exist for firms to tap into the green movement. On the regulatory side, for example, the European Union has regulations in place regarding the level of hazardous substances contained in the component of electronic equipments (RoHS, 2002), as well as the collection and recycling of such equipments circulated in the EU market (WEEE, 2002); these regulations have a profound impact on the way to design and evaluate supply chain processes (Krikke et al, 2003; Hervani et al, 2005). On the market side, several major logistics service providers, such as DHL, TNT, and UPS, all strive to improve their carbon efficiency and cut carbon emissions (Burnsed, 2008; Anonymous, 2008). Wal-mart also exerts its green influence over its extensive supply networks. It has launched several initiatives to demand its suppliers to reduce packaging, and to assist suppliers to meet local environmental regulations and social standards (Gillentine, 2007; Birchall, 2008).

In face of such growing and dynamic connotations associated with SCM, proper evaluation and design of supply chain processes have created great challenges to both managers and researchers. Managers need a comprehensive evaluation approach that can consider multiple input and output criteria set forth by different stakeholders. The approach should also correspond to the interrelated productive structure of a supply chain. In addition to the multi-criteria capability, the design approach is also expected to handle problems with limited information for decision-making. This thesis will develop approaches to tackle the above issues.

So how do we define the concept of performance? Neely et al (1995) provides a general definition of performance measurement:

> "*Performance measurement can be defined as the process of quantifying the efficiency and effectiveness of action.*" (Neely et al, 1995, p. 80)

In this definition, effectiveness pertains to how well the action contributes its nominal goal, and efficiency concerns the amount of resources used to complete the action. Accordingly, we can adapt this definition and define *measuring supply chain performance* as "*the process of quantifying the efficiency and effectiveness of supply chain operations.*"

Several studies in the literature have underlined the practical importance of supply-chain wide performance measures. Gunasekaran et al (2004) argue that frequent evaluation and benchmarking of supply chain outputs are necessary for companies to achieve their SCM objectives. Supply chain measures are crucial for the coordination of cross-functional and inter-organizational activities in SCM, and for forming long-term alliances among firms in the chain (Trent and Monczka, 1994; Gunasekaran et al, 2001). Performance measures at the supply chain level can serve to identify improvement opportunities, coordinate efforts of different parties, and make contracting and risk sharing justifiable in a supply chain. Finally, detailed activity analysis of supply chain processes can be time and resource consuming (Homburg, 2001). Supply chain measures can help supply chain members focus on primary symptoms at the supply chain level first, and then determine where to perform a more detailed activity analysis for the lower-level and firm-specific operations.

1.2 Performance characteristics of supply chain operations

As discussed earlier, supply chain management is a construct that has evolved overtime, and therefore it has different definitions, focus areas, and performance indicators for the supply chain process. Otto and Kotzab (2003), for example, summarize six major perspectives and the corresponding goals of SCM. In addition to the difference in perceptions, firms in a supply chain may apply firm-specific performance measures. From a supply chain viewpoint, these measures can lead to conflicting decisions and do not evaluate firm performance from the view at the supply chain level (Lee and Billington, 1992; Sabath and Fontanella, 2002). Juttner and Peck (2003) show that most companies manage their supply chain by product and channel type, so they tend to neglect firm interactions in managing their supply networks. Without a holistic view on performance, a supply chain can easily become sub-optimal and lose its long-term competitiveness (Filippini and Vinelli, 1998; Holmberg, 2000). Gunasekaran et al (2001) advocate the development of a performance measurement system, in which performance measures for the supply chain and individual firms coexist and are linked with each other. Beamon (1999) criticizes the pervasive use of a single cost-based performance measure in studies of supply chain modeling. He also suggests that multiple measures be used to fully reflect the broad strategic goal of SCM.

After developing performance metrics for different evaluated dimensions of a operation, it is important that the evaluation results are linked to either internal or external improvement processes. Johnston and Brignall (2002) and Smith and Goddard (2002b) argue that, to achieve continuous performance improvement, performance measurement should be carried out in connection with the analysis and response phases. Holmberg (2000) states that the departmental fragmentation within firms and the resultant confined views on performance have hindered the internal communication for a unified direction toward better corporate and supply chain performance.

Since a supply chain consists of a series of firms, it will perform only as well as its weakest link. The growing trend of outsourcing and globalized manufacturing have further fueled the proliferation of the supply chain processes across business and national boundaries. Thus actions and decision taken by one firm can considerably impact the performance of other firms (Norrman and Jansson, 2004); minor performance deterioration of a firm can snowball into a disaster for the entire supply chain. Mattel, the maker of the popular Barbie dolls and Hot Wheels cars, recalled nearly one million toys worldwide in August 2007, because the toys manufactured during a two-month period by its contracted vendors in China contained impermissible levels of lead (Story, 2007). Although these vendors had been working with Mattel for years, their improper sourcing decision, which allegedly caused these lead tainted toys, had a severe consequence for the entire supply chain. To ensure that no other flawed Mattel products were circulated in the market, Mattel launched global product testing and extended investigation on the manufacturing facilities of its major suppliers from China. These cases highlight that supply chain performance is susceptible to performance variations of the constituent members. As another example, in 2009, it is found that Sanlu, China's largest milk powder manufacturer had their product contaminated with melamine, a chemical hazardous to children's kidney systems (Branigan, 2008). The consequences of the incident were not limited to the Chinese market. Many food supply chains in the Asia-Pacific countries were severely disrupted, since Sanlu was their major supplier of dairy materials. Hundreds of products have been recalled, and the related financial loss and the number of victims are still growing. The consequences of performance variations include not only the direct costs of product recalls, but also loss of company's goodwill, which may take years to recover.

Firms at the downstream end of a supply chain are also critical in the quality and cost of services or products provided to customers—it is said that "20% of suppliers is responsible for 80% of the poor performance" (Handfield et al, 2000). GM's Service Parts Operations (SPO) provides automotive parts to GM dealers. In the early eighties SPO operated very efficiently and the service it provided to GM dealers was remarkably well. However the service that GM's end-customers received was constantly inferior to that of other competitors in the market, due to GM dealer's faulty inventory systems. GM's case also highlights the important role that the supplier selection process plays in affecting the product performance and that we should evaluate suppliers, and possibly even customers, in terms of the contribution they can offer to the supply chain, rather than to the buyer itself; see Hausman (2005).

We have discussed the issue about the sequential production structure that creates close interrelationships among firms in a supply chain; we have also talked about the performance characteristic that supply chain operations critically depend on firms in the chain family. On a less visible level, however, the growing complexity of supply chain structures also renders *time dynamics* an influential factor in SCM (Mason-Jones, 1999). Firms in a supply chain are autonomous or semiautonomous, so their decision-making processes are usually segmented and not fully coordinated. Their policy decisions[1] can therefore have a dynamic impact on their own performance, as well as on the performance of other firms in the supply chain, as can also be seen from Mattel's and Sanlo's cases. In addition, the investment in production facilities, IT system and initiatives to improve environmental performance can be realized across a period of time; see Chapter 3 and the references therein. The hierarchical production planning approach can also add to the dynamics in the supply chain system (Bitran and Tirupati, 1989; Anderson and Joglekar, 2005). The "chain" or "network" type of production creates performance interactions that ripple through time, organizational, and geographical dimensions; it also causes difficulties in accurately measuring supply chain performance.

1.3 Process design and resource allocation problems

Supply chain design and process development are among the most important strategic decisions in SCM, in that they blueprint the supply chain architecture. Fine (2000) recognizes supply chain design as the most fundamental competency of firms. He considers the capability of supply chain design not only vital for the survival of companies and industries, but also powerful enough to initiate shifts in industrial structures.

In practice, business process design and evaluation are closely related. Conceptually, "evaluation" and "design" very often differ only in the time of decision-making or execution (see, e.g., Huber and McDaniel, 1986). In this thesis, we consider process evaluation as the process to map a firm's current or past profile

[1] For example, changes of production processes, scheduling methods, or implementation of new IT systems; see Disney et al (2004).

to a specific space of criteria; process design is the inverse of the above relation, in which we attempt to find out solutions to attain desired performance levels (or in other words, the best option available). For example, managers often plan on improvement actions based on either evaluation or prediction of current or prior performance of the focal firm and its competitors. In addition, the evaluation outputs of the previously adopted design parameters can serve as the guideline for subsequent design decisions.

As a result of the difference in their decision timeframes, evaluation and design methods rely on different data requirements. Process evaluation can proceed by analyzing information available, such as expert viewpoints and the historical data of the organization, competitors and the industry. The key issue here is to systematically summarize or extract meaningful information from available data for the purpose of facilitating future decision-making. Process design, however, requires an estimate of the effect of the policies that will be implemented in the future. Furthermore, shortened product life cycles have induced frequent product introductions and technological innovations in today's turbulent market; fast decision-making and accelerated information obsolescence have both become commonplace.

The above discussion shows that the procedure used to handle multiple evaluation criteria plays a decisive role in the supply chain design and evaluation. As noted, SCM has been a growing concept with multiple facets. While increasing short-term profits has long been the prioritized area, managers are concerned with objectives such as superior customer satisfaction, product quality, and product's environmental impact are crucial to sustainable supply chain performance as well. For many of these objectives, however, it is usually difficult to put price tags on them and to pinpoint the trade-offs between them. The majority of supply design studies mostly consider only a monetary objective or an arbitrary linear combination of multiple objectives (e.g., Arntzen et al, 1995; Camm et al, 1997; Kim et al, 2002; Goetschalckx et al, 2002; Santoso et al, 2005). Thus we still need a sound methodology to handle the multi-dimension nature of process design and evaluation problems in a supply chain.

Sunil and Peter (2001) and Fine (2000) define supply chain design and reconfiguration as the ability to properly allocate internal resources and simultaneously integrate external resources to support the competitive strategy of the firm. This thesis follows this problem definition, and will present multi-criteria design approaches capable of handling design problems with incomplete information about the performance of different design options.

1.4 Methodologies

From the above discussions, we can summarize the issues about evaluating the performance of supply chain operations:

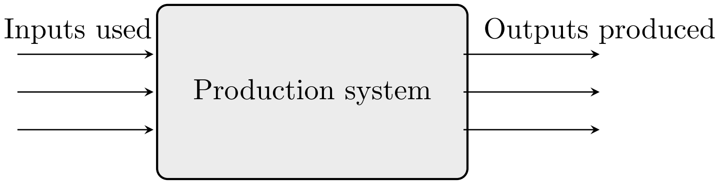
- *Supply chain operations involve multiple inputs and outputs of different firms at different times*
- *Dynamic impacts of one firm's performance on another (and on the chain)*
- *The performance evaluation and improvement actions should be coordinated across all levels of production in a supply network.*

For the process design, we need to pay attention to:

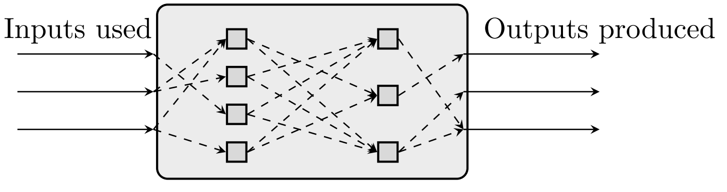
- *Decision-making with only limited information about the future performance of the system.*
- *Resource allocation decisions should consider the performance variations from other partner firms.*

To properly deal with multi-dimensionality, we need to consider multi-input and output factors of a production system. Figure 1.1 gives a general illustration of a multi-factor production system, which uses multiple inputs to produces multiple outputs. In this framework, we do not explicitly model the interior of the system, nor are we concerned about it—the evaluation is only carried out at the network level. This production model is called a "black-box" model.

In this thesis we use Data Envelopment Analysis (DEA) as the main vehicle of performance measurement. Conventional DEA models basically follow the above "black-box" construct to evaluate the relative efficiency of firms (Charnes et al, 1978). More specifically, the production capability of production units is formulated only under some general assumptions[2]. One salient advantage of DEA is that it can use a single index to assess the performance of production units that involve multiple inputs and outputs. DEA is also known to have several convenient advantages over other competing approaches to multi-factor performance evaluation; we will give a detailed discussion in Chapter 4. DEA has been widely used to evaluate different organizations, including universities, hospitals, financial institutions and manufacturing plants.[3] See Cooper et al (2006) for an introduction to DEA, and Gattoufi et al (2004) for a comprehensive bibliographical survey of DEA studies.



(a) DEA production model



(b) Two-tier supply network

Fig. 1.1. Comparison of the traditional DEA and the network models

[2] These assumptions on the production function include: monotonicity, convexity, envelopment and minimum extrapolation; see Banker (1993) for an explanation.

[3] The seminal DEA paper, Charnes et al (1978), has been the most-cited paper in the history of European Journal of Operations Research (totally 2427 cites on Feb 1 2009).

The above-mentioned advantages of DEA can nonetheless turn into limitations when we are dealing with supply chain problems. First, for simplicity, traditional DEA models have ignored the dynamic interrelations among operations over time, and therefore they assume that temporal production is independent—an assumption that clearly violates the dynamic nature of supply chain processes. In this thesis we will generalize the classical DEA model by incorporating dynamic parameters into evaluation. Second, former DEA models ignore the internal structure of evaluated units. In supply networks, we have explicit information about the internal sub-processes (see Figure 1.1). Although supply networks can be considered as the unit of analysis, as we will show later in Chapter 3, looking into the black box can yield additional opportunities to discover inefficiencies in the network that cannot otherwise be detected.

Although there has been a substantial body of DEA research, the idea of using DEA to assess the performance of production units with a complex production structure (e.g., supply chains or networks) has gained limited attention. Zhu (2002) proposes a value-chain DEA model to measure the performance of supply chain and its members; Chen and Zhu (2004) use the value-chain model to evaluate IT's impact on firm performance. Liang et al (2006) and Chen et al (2006) propose efficiency evaluation approaches for a two-tier supply chain model from a game theoretic perspective. Färe and Grosskopf (2000) and Castelli et al (2001, 2004) introduce the network DEA model, in which the interior structure of production units can be explicitly modeled. These studies tend to view supply chains as a sequence of static, but independent processes. Therefore, the "time" element is not considered in their analysis—as will be shown later in this thesis, omission of dynamics in production would lead to marked biased evaluation results.

Smith and Goddard (2002a) suggest that performance measures should be systematically deployed in a top-down fashion to ensure the organization is controllable and well coordinated. Supply chains similarly need a systematic structure of performance measures for different units, e.g., individual firms, tiers in the supply chain, and the whole chain. In this thesis we propose a hierarchical performance measurement system. In the system the supply chain measure gives the current state of supply chain performance, and the firm- and tier-specific measures help pinpoint the exact areas that can be improved. This measure can also facilitate communications among supply chain members, handling trade-offs among different partner and objectives, and, most importantly, coordinate efforts and development strategies for firms in a supply chain.

Several papers in the literature have integrated DEA with the process design methodology (Ross et al, 1998; Talluri and Baker, 2002; Narasimhan et al, 2005). These studies also point to an important characteristic, and in many cases a limitation of DEA and other methods for posterior evaluation of a process. In this kind of approach, managers can only take recourse actions for losses and inefficiency that have already occurred.

By joining simulation techniques with DEA, we can do preemptive planning for business processes, while considering the multi-dimensional trade-offs among performance indicators. DEA has well-developed statistical foundations, and therefore can be used in conjunction with the existing simulation algorithms and statistical inferences. The thesis studies two often-seen situations of information availability, each based on a different assumption on the non-deterministic environment. We illustrate the approaches by applications to warehouse planning and R&D project budgeting problems.

1.5 Synopsis of the thesis

The main text of this thesis consists of two parts, which cover evaluation methods for supply chains and approaches to process designs under uncertainty, respectively.

Part I of this thesis, which contains two chapters, introduces methodologies to evaluate the performance of supply chain (network) operations using DEA. Chapter 2 establishes the theories and methodologies to evaluate the efficiency of firms in dynamic production. The dynamics in production can be seen in most production processes in supply chains, and, if ignored, they can greatly impact the performance evaluation results. In particular, we focus on the situation where production inputs of a firm are dynamically linked to the firm's future output production. The empirical application of the adverting to sales process reveals that using the conventional DEA model can produce significantly biased evaluation results in dynamic production, which can seriously mislead subsequent decision-making. The content of this chapter is based on Chen and van Dalen (2009).

In Chapter 3, we adapt and extend the dynamic evaluation model for individual firms to that for production networks. In addition, this chapter has contributed to the development of economic properties of production networks. To construct a performance measurement system for supply chains, we develop a network evaluation model that comprises a system of dynamic measures for both the supply chain as a whole and (tiers of) firms in the chain. The system of dynamic efficiency measures aim to capture the performance at different levels of production and build the connections among them. The evaluation output for supply networks can be decomposed into componentwise measures that indicate the performance of individual firms (and individual tiers) in the supply network. This chapter is based on Chen (2009a).

In Part II we deal with the design problems in two specific situations of incomplete information: *risky* and *uncertain* environments. [4] In risky environments, the quantities of inputs and outputs of the production system are not known for sure, but can be represented by known stochastic processes. In uncertain environments, however, even representing these unknown quantities by stochastic processes becomes questionable. The design problems can be contrasted with the evaluation problems in Part I, where the inputs and outputs of the system are known. In the design problems, we evaluate the future, instead of past perfor-

[4] Knight (1921) distinguishes *risk* from *uncertainty*, as "Risk is the known chance of loss; uncertainty is what is unknown." I follow his terminology.

mance of production units. Instead of evaluating the outcomes, we evaluate the design alternatives.

In Chapter 4, we develop a multi-criteria evaluation framework for decision problems in the risky environment. We provide an application to the design of order picking systems in a warehouse considering three criteria: picking time, service level, and the number of items handled. In this environment, we have a finite number of design alternatives, and our goal is to select one of them according to estimations of the multiple inputs and outputs associated with each design option. Unlike most studies in the literature, which search for the best choice only, our framework identifies top groups of superior policies for managers to choose from.

This feature is crucial for several reasons. First, it can be computationally expensive to screen out the best from a vast pool of available policies. Our approach reduces the selection range to a manageable size specified by the manager. Second, the best policy may not be robust when the operational environments change (e.g., changing order frequencies and quantities). So managers can obtain more flexibility from a larger choice set, as compared to a single choice, when changes in the environment are expected. In addition, by examining the performance of policies in the subset, managers can also gain deeper insight into the performance of all available policies. Third, performance of production processes are often subject to factors that are difficult to model quantitatively (e.g., feasibility of implementation, and hidden costs). Therefore it is important that we make use of managers' tacit knowledge and experience with the environment in the design process. Our proposed framework incorporates DEA, simulation and statistical techniques to help managers make design decisions with enhanced flexibility and efficiency. The content of this chapter is based on Chen et al (2009).

In Chapter 5, we tackle the design problem in the uncertain environment. Compared to the risky problem, the uncertain environment does not allow to model uncertain factors in the system by known stochastic processes. Instead, we have one sample of the production factors of available policies or designs. The values of the input-output variables can come from historical records or simply a subjective estimation given by the management team. This situation can usually be seen, for example, in new product development processes and configuring supply chains for new products or services, where information resources are either limited or based on a rough prediction. In this chapter, we bootstrap an improved DEA bootstrap algorithm to properly assess the efficiency and the associated variation of each unit. We also develop decision models that can make design decisions based on bootstrap efficiency distributions.

In this chapter we provide two applications based on the DEA bootstrap method. First we consider the problem of allocating limited funding to a number of projects according to their required funding and expected contributions. In the chapter, we evaluate the performance of all projects by the DEA approach, but the performance portfolios of resource allocation are estimated by the bootstrap efficiency results (i.e, bootstrap mean and (co)variance). The final allocations are determined by the Markowitz mean-variance model to optimize the trade-off between risk and mean efficiencies. Our bootstrap algorithm is non-parametric, and hence the bootstrap distributions are usually non-normal. Many statistical inferential methods, however, are constructed on the foundation of a normality (or multi-normality) assumption. In view of this issue we also develop a batch-means algorithm to transform the bootstrap distributions to normal distributions. The bathed bootstrap distributions are then amenable to a wide range of statistical techniques that require a normality assumption. The content in this chapter is based on Chen (2009b).

Finally, in Part III we sum up the thesis and point out promising directions for theoretical and empirical extensions.

Part I

Evaluating dynamic and network production systems

2

Measuring the dynamic performance of firms

Dynamics in production processes have been an important but often ignored property in performance evaluation. To accurately measure performance of firms, the dynamic interrelations should be incorporated into the efficiency measure. Existing data envelopment analysis (DEA) approaches, however, assume no dynamics and rely on a static production environment. These approaches can easily lead to biased evaluation results due to the erroneous modeling assumption. To tackle this issue, we develop a dynamic DEA model to allow intertemporal effects in efficiency measuring. In the model, we use a linear parametric formulation to transform the dynamic problem into a static one; we also formulate the panel vector autoregressive model (PVAR) to estimate the lag parameters in the parametric formulation. We demonstrate our methodology by evaluating advertising efficiencies of several major automobile and pharmaceutical firms in North America. The result shows that using static DEA in dynamic production can lead to both rank reversals and changes in efficiency scores.

2.1 Introduction

Data Envelopment Analysis (DEA) has been widely used to measure relative performances of productive units in the general multi-input, multi-output situation (see Gattoufi et al, 2004 for a recent bibliography). Despite their widespread popularity, the classical DEA model and its extensions, however, operate under the implicit assumption that production technologies are static and independent across time. Researchers have thus ignored an important factor in efficiency measuring processes: *lagged productive effects*. Lagged productive effects (hereafter lagged effects) occur when inputs contribute to both current and future output production. As nearly all economic situations have dynamic components, lagged effects can arise in many real-world situations; for instance, the impact of accumulated knowledge and R&D activities on economic growth and productivity improvement (Adams, 1990; Romer, 1990; Huergo and Jaumandreu, 2004), dynamic production processes (Landesmann and Scazzieri, 1996), the effect of human resource practices on firm performance (Huselid and Becker, 1996; Ichniowski et al, 1997), advertising-to-sale effect (Clarke, 1976; Dekimpe and Hanssens, 1999; Feinberg, 2001) and IT investment and firm performance (Devaraj and Kohli, 2000, 2003). The principle of systems thinking also emphasizes the importance of identifying the feedback relationships among different interacting components in a complex system (Gharajedaghi, 2006). These examples signify that acknowledgement of lagged effects is essential for the analysis of dynamic systems, and that naive simplifications of dynamic systems can result in misestimations of system performance.

Notwithstanding their theoretical importance, lagged effects have only received limited attention in the DEA literature. Golany (1988) briefly describes lagged effects of advertising on sales to illustrate the ordinal relation among multipliers in DEA models (i.e., the effect of one-time advertising decreases over time). However, he did not continue to further formalize the notion of lagged effects. Färe et al (1996) propose a dynamic production model that consists of a sequence of static production technologies—these time-specific technologies are connected by storable inputs and intermediate outputs from individual periods. While their model has a time dimension, Färe et al. consider lagged effects in an intrinsically static production construct (i.e., storable inputs are budgetary, and intermediate outputs are known beforehand); so do other studies that focus on the effect of quasi-fixed inputs (e.g., Nemoto and Goto, 2003; Sueyoshi and Sekitani, 2005). Emrouznejad and Thanassoulis (2005) evaluate the efficiency of dynamic production processes by designating intertemporal inputs and outputs as additional variables in the static DEA model. In this setting, however, the dimension of the solution space increases multiplicatively with the numbers of inputs, outputs and evaluation periods; thus their model will easily lose its discrimination power. More recently, Chen (2009a) proposes a model to evaluate the performance of a dynamic production network that consists of multiple sub production units. He develops a new efficiency index to incorporate lagged effects in performance evaluation, but he does not provide a method to determine lag parameter values in the index.

Moreover, as most conventional DEA models presume a static production technology, studies that use conventional DEA models to evaluate the longitudinal performance and productivity change have implicitly imposed that production technologies are temporally independent (e.g., Sueyoshi, 1997; Thursby and Thursby, 2002; Banker et al, 2005). This concern is further exacerbated by the fact that empirical data used in these studies are structured according to some predetermined cyclic conventions (e.g., monthly or yearly intervals). So the observation cycles may not always synchronize with the duration of productive effect. Thus we need a more general model to measure the efficiency of dynamic production processes.

This chapter develops an integrated approach to estimate the efficiency of decision-making units (DMUs) in dynamic production. Our approach can capture the dynamic productive relationship based on ordinary input-output panel data. In addition, we also want to find out the conditions under which the lagged effect may have no impact on the efficiency evaluation result. Specifically, we formulate lag parameters through a parametric form of linear optimization. Implementing the dynamic DEA model, however, requires knowledge of the lag parameters as input values. As a means to estimating lag parameter values, we apply a panel Vector Autoregressive (PVAR) model to empirical input-output data. Efficiency scores can be obtained from the dynamic DEA model with its parameters substituted by the estimates from the PVAR model. Our approach can be contrasted the traditional regression approach, which allows only a single output variable and, more importantly, is based on the static production assumption as well (see Coelli, 2005). We should note that our index is different from the effect of frontier shifts and productivity changes as put forward in the Malmquist productivity index, since the production frontier in the index is still estimated based on the static DEA model.

We also develop the dynamic production model for the analysis of technical efficiency. The resultant dynamic DEA model is a generalization of static DEA models developed since Charnes et al (1978). We also show that the dynamic DEA model has well-behaved topological properties, which provide a firm foundation for the analysis of efficiencies under lagged effects. The empirical application of our methodology—in which we evaluate advertising efficiencies of several major automobile and pharmaceutical firms in North America—reveals that static DEA models can lead to biased efficiency results in terms of both rankings and efficiency changes in dynamic production.

This chapter is organized as follows. In Section 2 we provide an overview on the static DEA framework, and follow to develop the dynamic DEA model in Section 3. In Section 4 we introduce the PVAR model used to estimate lag parameter values. In Section 5 we illustrate the methodology by an empirical application to evaluating the advertising efficiencies of several major automobile and pharmaceutical firms in North America. This chapter ends with a summary in Section 6.

2.2 Conventional DEA framework

Before presenting our dynamic DEA model, we introduce relevant notations of static production technologies and efficiency measuring in this section. These basic ideas are also essential for the construction of our extended model.

We first define static production technologies. In period t_a, consider a group of K DMUs, $k = 1, \ldots, K$, each using inputs $\mathbf{A}_k^{t_a} = [A_{kp}^{t_a}]_{p=1}^{I} \in \Re_+^I$ to produce outputs $\mathbf{S}_k^{t_a} = [S_{kq}^{t_a}]_{q=1}^{J} \in \Re_+^J$. DMUs are assumed to be homogeneous; that is, they produce a common set of outputs with a common set of inputs under an identical production technology. The observed ordered pair $(\mathbf{A}_k^{t_a}, \mathbf{S}_k^{t_a})$ is regarded as a feasible production plan; the collection of all feasible production plans forms the production possibility set (PPS) under the current production technology. Formally, the PPS in the static DEA framework can be expressed as:

$$\mathrm{PPS}^{t_a} := \{(\mathbf{A}_k^{t_a}, \mathbf{S}_k^{t_a}) : \mathbf{A}_k^{t_a} \text{ can produce } \mathbf{S}_k^{t_a}\}, \tag{2.1}$$

Given the PPS, we can define two set mappings between input and output vectors:

$$\begin{aligned} L(\mathbf{A}_k^{t_a}) &:= \{\mathbf{S}_k^{t_a} : \mathbf{A}_k^{t_a} \in \Re_+^I, (\mathbf{A}_k^{t_a}, \mathbf{S}_k^{t_a}) \in \mathrm{PPS}^{t_a}\} \; \textit{(output possibility set)}, \\ L'(\mathbf{S}_k^{t_a}) &:= \{\mathbf{A}_k^{t_a} : \mathbf{S}_k^{t_a} \in \Re_+^J, (\mathbf{A}_k^{t_a}, \mathbf{S}_k^{t_a}) \in \mathrm{PPS}^{t_a}\} \; \textit{(input requirement set)}. \end{aligned} \tag{2.2}$$

These two mappings together give two dual perspectives on the temporal PPS—we can either examine input requirements or output possibilities to characterize the PPS. Note that production technologies defined in (2.1) and (2.2) are static; i.e., productions in different periods are independent. To contrast the static with the dynamic production model, we temporarily drop the time superscripts from the notations, and we will resume the time-specific notation in the next section.

Given the PPS, the efficiency of a production plan can be determined by comparing its position in the PPS with its benchmark on the production frontier—the frontier is defined as the boundary set of the PPS in $\Re_+^I \times \Re_+^J$, and production plans in the frontier set are considered efficient. The output-oriented benchmark of $(\mathbf{A}_k, \mathbf{S}_k)$ is the production plan that uses $\mathbf{A}_k$ to produce the output level equal to the maximally expanded $\mathbf{S}_k$ in the PPS. Therefore, given current inputs, the output-oriented efficiency is defined to be the maximum expansion multiplier of current outputs, and the efficiency score can be obtained from the optimization problem (see, e.g., Farrell, 1957):

$$\max_{\theta_k \in \Re} \big\{ \theta_k : \theta_k \mathbf{S}_k \in L(\mathbf{A}_k) \big\}. \tag{2.3}$$

Charnes et al (1978) operationalized this construct by characterizing PPS as a polyhedral cone generated by the set of observed production plans; the corresponding output possibility set can be expressed as:

$$\begin{aligned} L_{CCR}(\mathbf{A}_k) := \big\{ \mathbf{S}_k : & \sum_{i=1}^{K} \lambda_i A_{ip} \le A_{kp},\ p = 1, \ldots, I, \\ & \sum_{i=1}^{K} \lambda_i S_{iq} \ge S_{kq},\ q = 1, \ldots, J, \\ & \lambda_i \ge 0,\ i = 1, \ldots, K \big\}. \end{aligned} \tag{2.4}$$

Constraints in formulation (2.4) specify that the PPS is the minimal enveloping set containing all observed production plans, and closed under non-negative linear combinations. In this setup, the PPS conforms to the constant returns-to-scale (CRS) assumption, because nonnegative scalar multiples of production plans again belong to the PPS.

By the construction of (2.4), the efficiency of an evaluated production plan can be computed by solving an LP version of problem (2.3) with $L(\mathbf{A}_k)$ defined by $L_{CCR}(\mathbf{A}_k)$. In particular, the output-oriented efficiency of DMU-k can be evaluated by solving the LP problem:

$$f_k\Big((\mathbf{A}_i, \mathbf{S}_i)_{i \in K} \Big) := \max_{\theta_k \in \Re, \lambda_i} \Big\{ \theta_k : \theta_k \mathbf{S}_k \in L_{CCR}(\mathbf{A}_k) \Big\} = \theta_k^*. \tag{2.5}$$

Problem (2.5) is known as the CCR model in the literature: $\theta_k^* \mathbf{S}_k$ is the image of S_k under the transformation that projects it to the production frontier. DMU-

k is efficient if θ_k^* is equal to one[1]; if θ_k^* greater than one, it means that DMU-k can increase its outputs proportionately by a factor θ_k^* with its current input levels. Note that the validity of using θ_k^* as an efficiency index hinges on the static production assumption as defined in (2.4); i.e., no lagged effect exists in production. Furthermore, the CCR model (2.5) is written in the linear parametric form. This makes it easy to see, in the static DEA framework, that the efficiency measurement is parameterized by the observed input-output pairs in the same period. We will use this parametric form to introduce lagged effects into the efficiency measurement.

2.3 Dynamic production theory and dynamic DEA model

Based on the static production framework, this section sets up the dynamic DEA model, which can be used to evaluate efficiencies under the influence of lagged effects. The dynamic DEA model captures the intertemporal relation between inputs and outputs in dynamic production processes. We will first define lag parameters, and then continue to formulate the dynamic DEA model.

2.3.1 Parameters for lagged effects

Consider a dynamic production process observed from periods t_0 to t_n. For an arbitrary time period t_a, the m-period lag model depicts a production process, in which inputs used in period t_a can contribute to output production in periods t_a, $t_{a+1}, \ldots, t_{a+m}$, with $a + m \leq n$. Formally, we represent the productive effects of a specific input p of DMU-k at time period t_a by a J-by-m matrix

[1] We can further distinguish the "strong efficiency" (or "Pareto-Koopmans efficiency") condition from this general efficiency definition (i.e., weak efficiency). In the former, the efficiency value θ_k^* is one, and all slacks variables in the optimal solution to the LP problem (2.5) also have to be zero.

$$\mathbf{D}_{kp}^{t_a} = \begin{bmatrix} D_{kp}^{t_a}(1,0) & D_{kp}^{t_a}(1,1) & \cdots & D_{kp}^{t_a}(1,m) \\ D_{kp}^{t_a}(2,0) & D_{kp}^{t_a}(2,1) & \cdots & D_{kp}^{t_a}(2,m) \\ \vdots & \vdots & \ddots & \vdots \\ D_{kp}^{t_a}(J,0) & \cdots & \cdots & D_{kp}^{t_a}(J,m) \end{bmatrix}, \text{ and } \mathbf{D} := [\mathbf{D}_{kp}^{t_a}]_{p=1}^{I}. \tag{2.6}$$

Specifically, for input $A_{kp}^{t_a}$, $p = 1, \ldots, I$, the entry $D_{kp}^{t_a}(q,r)$ is the degree of output augmentation of $S_{kq}^{t_{a+r}}$ associated with the input p, as compared with the input's aggregate productive effect over $t_a, \ldots, t_{a+m}$. So $D_{kp}^{t_a}(q,r)$ corresponds to input p's dynamic impact on the production of output q in t_{a+r}, and its value can be interpreted as the relative intensity of the dynamic productive effect in t_{a+r} (i.e., the larger the value, the stronger the effect). $\mathbf{D}$ denotes the collection of all lag parameters in the production process. We assume that strong output disposability (e.g., Färe et al, 1996, Chap. 2) holds in dynamic production processes; therefore $D_{kp}^{t_a}(q,r)$ are nonnegative numbers. Also note that, by the Axioms of Production (e.g., Färe et al, 1996, p.12), each row of $\mathbf{D}_{kp}^{t_a}$ is a semi-positive vector.

According to the time dimension, productive effects described in $\mathbf{D}$ can be divided into contemporaneous and lagged effects. The first category pertains to the concurrent output enhancement, as in the conventional DEA framework (2.4)–(2.5). These contemporaneous effects corresponds to the first column of $\mathbf{D}_{kp}^{t_a}$ for all inputs. An example for that is using fuel (input) to generate power and heat (outputs) in one period. The second category of productive effects involves the dynamic connection between the current input consumption and the output production in future periods. These dynamic effects are represented by the columns of $\mathbf{D}_{kp}^{t_a}$ beyond the first column. So the static production technology may be regarded as an extreme case, in which all matrices associated with inputs are componentwise zeros except the first column. For dynamic production, both types of productive effects can coexist. Figure 2.1 demonstrates these two types of factors: the solid lines represent the concurrent effects, and the dashed lines the lagged effects.

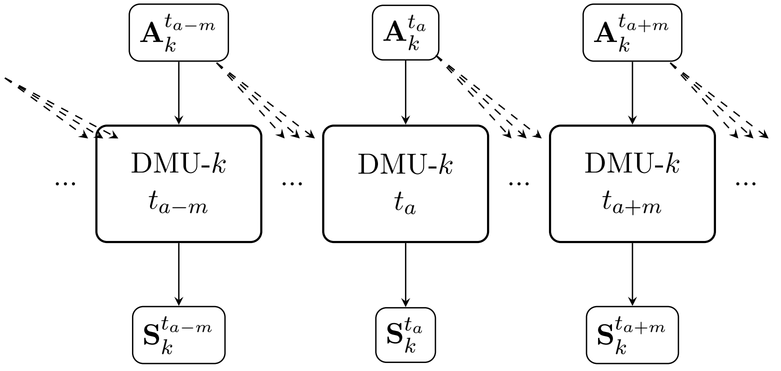


Fig. 2.1. Illustration of the m-period lag model

To convey our key ideas of the dynamic model more easily, we simplify notation by assuming that the dynamic parameters can be considered invariant with respect to their starting times and across different DMUs. It is important to note that, however, the method and model introduced in subsequent discussions are still valid in the general setting without this assumption. Specifically, we then have

$$\mathbf{D}_{kp}^{t_a} = \mathbf{D}_{k'p}^{t_a} = \mathbf{D}_p,\ \forall \text{ DMUs } k \text{ and } k', \text{ all inputs } p, \text{ and all periods } t_a. \tag{2.7}$$

With the homogeneity of DMUs, the total number of parameters is reduced to $IJ(m+1)$, and we can drop the superscript t_a and the subscript k from the dynamic effect matrix (i.e., $\mathbf{D}_p$).

2.3.2 Dynamic production and efficiency measuring

We now introduce the PPS in dynamic production. In view of the output-oriented perspective, we consider the dynamic productive effect as a specific source of variation in outputs. Let g_m be a class of functions representing output perturbations due to lagged effects. The modified PPS can be written as:

$$\widetilde{PPS}^{t_a} := \{(\mathbf{A}_k^{t_a}, \tilde{\mathbf{S}}_k^{t_a}) : \mathbf{A}_k^{t_a} \text{ can produce } \tilde{\mathbf{S}}_k^{t_a}\}, \tag{2.8}$$

and the corresponding output possibility set can be defined as

$$\tilde{L}(\mathbf{A}_k^{t_a}) := \Big\{ \tilde{\mathbf{S}}_k^{t_a} : \sum_{i=1}^{K} \lambda_i A_{pi}^{t_a} \leq A_{pk}^{t_a},\ p = 1, \ldots, I, \tag{2.9a}$$

$$\sum_{i=1}^{K} \lambda_i \tilde{S}_{iq}^{t_a} \geq \tilde{S}_{kq}^{t_a},\ q = 1, \ldots, J, \tag{2.9b}$$

$$\lambda_i \geq 0,\ i = 1 \ldots, K, \tag{2.9c}$$

$$\tilde{S}_{iq}^{t_a} = g_m\Big([S_{iq}^{t_r}]_{r=a}^{a+m}, \mathbf{D}\Big),\ i = 1, \ldots, K \Big\}. \tag{2.9d}$$

For conciseness, we denote the cross-sectional input-output data by $\mathbf{A}^{t_r} = [\mathbf{A}_i^{t_r}]_{i=1}^{K}$ and $\mathbf{S}^{t_r} = [\mathbf{S}_i^{t_r}]_{i=1}^{K}$, respectively. In the spirit of (2.5), the output-oriented dynamic efficiency $\tilde{\theta}_k^{t_a}$ of DMU-k at time t_a can then be obtained from the optimization problem:

$$\tilde{f}_k\Big([\mathbf{A}^{t_r}, \mathbf{S}^{t_r}]_{r=a}^{a+m}, \mathbf{D}\Big) := \max_{\tilde{\theta}_k^{t_a} \in \Re, \lambda_i} \Big\{ \tilde{\theta}_k^{t_a} : \tilde{\theta}_k^{t_a} \tilde{\mathbf{S}}_k^{t_a} \in \tilde{L}(\mathbf{A}_k^{t_a}) \Big\}. \tag{2.10}$$

Formulation (2.10) requires two arguments to evaluate efficiencies: (i) panel input-output data of all DMUs, and (ii) values of lag parameters. $\tilde{\mathbf{S}}_k^{t_a}$ is the image of the function g_m, whose domain consists of the set of lag parameters representing the dynamic input-output relations, and the output vectors $\mathbf{S}_k^{t_r}$ for $r = a, \ldots, a{+}m$. Additionally, through equation (2.9d), we establish the dynamics of efficiencies: the efficiencies at time t_a depend on the panel input-output data for the next m periods, to an extent contingent on the lag parameters $\mathbf{D}$. Given the lag parameter values, formulation (2.10) can be solved as an LP problem. However, we can expect that the dynamic DEA (2.10) in general will not be equivalent to the static DEA model (2.5), because the output matrix and the PPS are perturbed by lag parameters through function g_m in the dynamic DEA model. Also, given the finite panel of n periods, we do not have complete information required for efficiency evaluations over the last m of the n periods (c.f. (2.9d)), unless the productions of all DMUs stop after the observation window t_n.

We have completed the formulation of dynamic DEA models. Now, to evaluate efficiencies by the dynamic model, we need to specify g_m. Since the lag parameters are introduced as fractions of period-specific output contribution from inputs in different periods, we formulate g_m having the following functional form:

$$\begin{aligned}
\tilde{S}_{kq}^{t_a} &= g_m\Big([S_{kq}^{t_r}]_{r=a}^{a+m}, \mathbf{D}\Big) \\
&= \Big(\sum_{r=0}^{m}\sum_{p=1}^{I} D_p(q, r+1) S_{kq}^{t_{a+r}}\Big) \Big/ \Big(\sum_{r=0}^{m}\sum_{p=1}^{I} D_p(q, r+1)\Big) \\
&= \sum_{r=0}^{m}\Big(\sum_{p=1}^{I} D_p(q, r+1)\Big) S_{kq}^{t_{a+r}} \Big/ \sum_{r=0}^{m}\Big(\sum_{p=1}^{I} D_p(q, r+1)\Big) \\
&= \sum_{r=0}^{m} \omega_q(r+1) S_{kq}^{t_{a+r}}, \text{ where } \sum_{r=0}^{m}\omega_q(r+1) = 1,
\end{aligned} \tag{2.11}$$

$D_p(q, r)$ denotes the rth entry of the qth row of $\mathbf{D}_p$ and $\omega_q(r)$ is a scalar. In the second equality of (2.11), we can express $\tilde{S}$ as a weighted ratio of outputs produced in t_a, $t_{a+1}, \ldots, t_{a+m}$, with the weights determined by the sum of lag parameter values associated with the productions of output q in these lag periods. Furthermore, by the nonnegativity of $\mathbf{D}_p$, it also holds that $0 \le \omega_q(r) \le 1$ for all r and $\sum_{r=1}^{m+1}\omega_q(r) = 1$. Therefore, for each output q, the parameter set $\omega_q := [\omega_q(r)]_{r=1}^{m+1}$ is a bounded polyhedron in $\Re_+^{m+1}$, since it is formed by the intersections of finitely many hyperplanes and halfspaces. Furthermore, it is important to note that, by the functional form of (2.11), it suffices to estimate the $(m+1)$-dimensional vectors ω_q for all q to calculate (2.10); we will see later in our application that this feature enhances flexibility in estimating lag effects needed for the dynamic DEA model.

The structure of equation (2.11) has further implications in efficiency evaluations. First, the dynamic model (2.10) is a generalization of the CCR model (2.5). Specifically, the following theorem is immediate from these two formulations:

Theorem 2.1. *$f_k([\mathbf{A}^{t_a}, \mathbf{S}^{t_a}]) = \tilde{f}_k([\mathbf{A}^{t_r}, \mathbf{S}^{t_r}]_{r=a}^{a+m}, \mathbf{D})$ for $k = 1, \ldots, K$ and any $\mathbf{D} \in \Re_+^{IJ(m+1)}$, if one of the following conditions is true: (i) for $q = 1, \ldots, J$, vectors ω_q in (2.11) equal to unit vectors $e_1 \in \Re_+^{m+1}$, and (ii) for a positive constant α_r, $[\mathbf{A}_k^{t_a}, \mathbf{S}_k^{t_a}] = \alpha_r[\mathbf{A}_k^{t_r}, \mathbf{S}_k^{t_r}]$ for $r = a+1, \ldots, a+m$ and all k.*

Proof. The proof is straightforward from inspecting (2.4), (2.9), and (2.11).

Theorem 2.1 states two situations where the dynamic and static DEA formulations are equivalent: either when (i) the production technology is fully static, or when (ii) the dynamic production process repeatedly replicates the current situation through multipliers α_r. Furthermore, if the condition in the theorem holds, then $f_k([\mathbf{A}^{t_a}, \mathbf{S}^{t_a}]) = f_k([\mathbf{A}^{t_{a+1}}, \mathbf{S}^{t_{a+1}}]) = \ldots = f_k([\mathbf{A}^{t_{a+m}}, \mathbf{S}^{t_{a+m}}])$ for all DMUs k; by Theorem 2.1, this can further lead to similar equivalence conditions for $\tilde{f}_k$ over the periods of observation.

We can also see that $\tilde{S}_{kq}^{t_a}$ is a convex combination of the outputs produced in m lagged periods for output q. Therefore $\tilde{S}_{kq}^{t_a}$ is bounded within the closed interval $[\min_r\{S_{kq}^{t_r}\}, \max_r\{S_{kq}^{t_r}\}]$, for $r = a$ to $a+m$. In this setting, the same outputs produced in different periods are considered additive and of equal productive value. Additionally, the productive effects in different periods are depleted during their periods of effectiveness; therefore there is no compounding productive effect. After defining lag parameters and the dynamic DEA model, we are ready to investigate the properties of the dynamic DEA model.

2.3.3 Properties of dynamic DEA models

We first give a geometrical interpretation of the relation between lag parameters and output vectors; we then show several efficiency properties of the dynamic DEA model.

Let us first consider the simple one-period lag model ($m = 1$). Following (2.10) and (2.11), the one-period lag model is formulated as:

$$\begin{aligned}
&\tilde{f}_k\Big([\mathbf{A}^{t_j}, \mathbf{S}^{t_j}]_{j=a}^{a+1}, \omega_q = \big(\omega_q(1), \omega_q(2)\big),\ \text{for any output } q\Big) \\
&= \max_{\tilde{\theta}_k^{t_a} \in \Re, \lambda_i} \Big\{ \tilde{\theta}_k^{t_a} : \text{constraints (2.9a) to (2.9c)}, \\
&\qquad \tilde{S}_{iq}^{t_a} = \omega_q(1) S_i^{t_a} + \omega_q(2) S_i^{t_{a+1}},\ i = 1, \ldots, K,\ q = 1, \ldots, J \Big\}.
\end{aligned} \tag{2.12}$$

In model (2.12), the productive contribution of current inputs is limited to the production in the current and the adjoining period. Correspondingly, for each output q, problem (2.12) has two lag parameters: $\omega_q(1)$ and $\omega_q(2)$. Now consider two hypothetical situations: (i) the production technology is static; i.e., $\omega_q = (1, 0)$, for any output q, and (ii) the production technology is fully lagged by one period; i.e., $\omega_q = (0, 1)$, for any output q. In the first case, the optimization problem becomes:

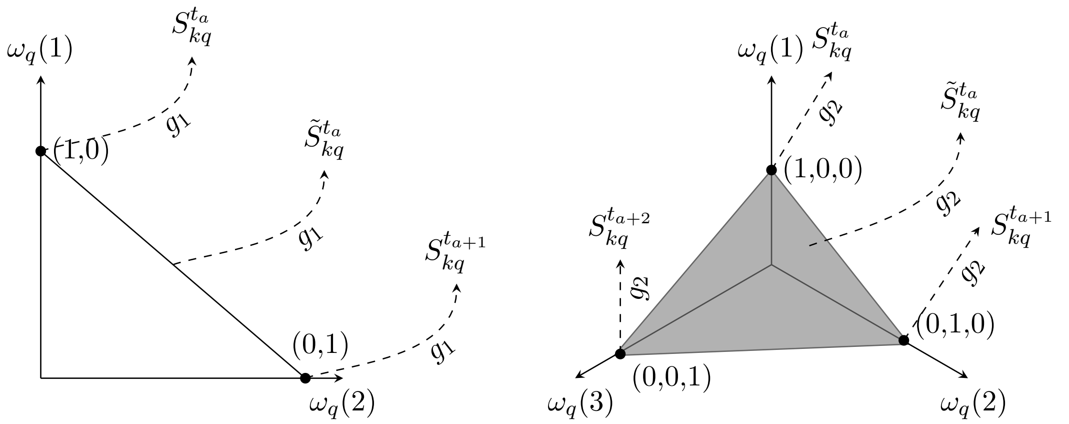
$$\begin{aligned}
&\tilde{f}_k\big([\mathbf{A}^{t_r}, \mathbf{S}^{t_r}]_{r=a}^{a+m}, \omega_q = (1, 0),\ \text{for any output } q\big) \\
&= \max_{\tilde{\theta}_k^{t_a} \in \Re, \lambda_i} \Big\{ \tilde{\theta}_k^{t_a} :\ \text{constraints (2.9a) and (2.9c)}, \sum_{i=1}^{K} \lambda_i S_{iq}^{t_a} \geq \tilde{\theta}_k^{t_a} S_{kq}^{t_a}, \forall q \Big\}
\end{aligned} \tag{2.13}$$

In the second situation, the problem is:

$$\begin{aligned}
&\tilde{f}_k\big([\mathbf{A}^{t_r}, \mathbf{S}^{t_r}]_{r=a}^{a+m}, \omega_q = (0, 1),\ \text{for any output } q\big) \\
&= \max_{\tilde{\theta}_k^{t_a} \in \Re, \lambda_i} \Big\{ \tilde{\theta}_k^{t_a} :\ \text{constraints (2.9a) and (2.9c)}, \sum_{i=1}^{K} \lambda_i S_{iq}^{t_{a+1}} \geq \tilde{\theta}_k^{t_a} S_{kq}^{t_{a+1}}, \forall q \Big\}
\end{aligned} \tag{2.14}$$

Specifically, formulation (2.13) amounts to the conventional efficiency measurement under a static production technology. By contrast, in formulation (2.14), $\omega_q(1) = 0$ for any output q implies that the concurrent productive effect is nil; i.e., inputs contribute entirely to the output production in the next period.

In the previous section, we have pointed out that, for any output q and DMU-k, output levels obtained from g_m are bounded by the range of output levels in the current and the lag periods. Here, in the one-period lag model, we can further observe that the values of lag parameters ($\omega_q(1)$ and $\omega_q(2)$) correspond in time to output vectors used in the formulations ($S_{kq}^{t_a}$ and $S_{kq}^{t_a+1}$). Figure 2.2 graphically illustrates the relation for the one-period and two-period lag models.



(a) One-period lag model ($m = 1$) (b) Two-period lag model ($m = 2$)

Fig. 2.2. The parameter set of the one-period and two-period lag models

More generally, in the m-period lag model, we can associate $m+1$ output vectors of each DMU with the period-specific lag parameters in $\Re_+^{m+1}$. In particular, the lag parameter space of ω_q is a simplex in $\Re_+^{m+1}$, and output vectors $S_{kq}^{t_a+r}$, $r = 0, \ldots, m$, correspond to $m+1$ extreme points in the parameter space of ω_q in $\Re_+^{m+1}$.

For a description of the output possibility set, we already know that $\tilde{S}_{kq}^{t_a}$ lies between the end points of the value range of output levels in the lag periods. From (2.9a)–(2.9c), the output possibility of each DMU is actually a convex cone in $\Re_+^J$. We summarize this main fact in Theorem 2.2.

Theorem 2.2. *Given* $[\mathbf{A}^{t_r}, \mathbf{S}^{t_r}]_{r=a}^{a+m}$*, the production possibility set of the dynamic DEA model* (2.10) *is a convex cone in* $\Re_+^{I+J}$.

Proof. The production possibility set of (2.10) can be denoted as

$$\left\{ \Big(\sum_{i=1}^{K} \lambda_i \mathbf{A}_i^{t_a}, \sum_{i=1}^{K} \lambda_i \tilde{\mathbf{S}}_i^{t_a} \Big) : \lambda_i \geq 0, \text{for } i = 1, \dots, K \right\}, \tag{2.15}$$

which is clearly a subset of $\Re_+^I \times \Re^J$. Expanding the terms associated with output vectors according to (2.11), we have

$$\sum_{i=1}^{K} \lambda_i \tilde{\mathbf{S}}_i^{t_a} = \sum_{i=1}^{K} \lambda_i \omega_q \cdot [\mathbf{S}_i^{t_a}, \mathbf{S}_i^{t_{a+1}}, \dots, \mathbf{S}_i^{t_{a+m}}]'. \tag{2.16}$$

Given the nonnegativity of ω_q and $\mathbf{S}_i^{t_a}$, the production possibility set is a convex cone in $\Re_+^{I+J}$ generated by the $(I + J)$-dimensional vectors $(\mathbf{A}_i^{t_a}, \omega_q \cdot [\mathbf{S}_i^{t_a}, \mathbf{S}_i^{t_{a+1}}, \dots, \mathbf{S}_i^{t_{a+m}}]')$, for $i = 1, \dots, K$.

Theorem 2.2 describes the topological nature of the production possibilities in the dynamic setting. Our next result provides the theoretical basis for the analysis of dynamic efficiencies.

Theorem 2.3. $\tilde{f}_k$ *in the dynamic DEA model* (2.10) *is a continuous function on the lag parameter space.*

Proof. With a slight abuse of notation, we can express $\tilde{f}_k$ as $f_k(g_m(\cdot))$. Since f_k in (2.5) and g_m in (2.11) are both continuous functions (see Scheel and Scholtes, 2003), their composition $f_k(g_m(\cdot))$ is also continuous.

By the Intermediate-value Theorem and the convexity of parameter sets, one useful corollary follows from the preceding theorem.

Corollary 2.4. *Let* $\Omega = [\omega_q]_{q=1}^{J}$ *and* $\Omega' = [\omega'_q]_{q=1}^{J}$ *be two lag parameter matrices as defined in* (2.11)*. For arbitrary DMUs* i *and* j*, if* $\tilde{f}_i(\cdot, \Omega) > \tilde{f}_j(\cdot, \Omega)$ *and*

$\tilde{f}_i(\cdot, \Omega') < \tilde{f}_j(\cdot, \Omega')$, then there exists an $\Omega'' := \lambda\Omega + (1-\lambda)\Omega'$ for some $\lambda \in (0,1)$, such that $\tilde{f}_i(\cdot, \Omega'') = \tilde{f}_j(\cdot, \Omega'')$.

The "$\cdot$" in the corollary represents all other parametric arguments necessary for $\tilde{f}_k$; see formulation (2.10). Note that Ω'' is well-defined by the polyhedral convexity of the parameter set. Corollary 2.4 states that, when the order of the efficiencies scores of two DMUs alters under two sets of different lag parameters, there exists an intermediate parameter matrix with which the efficiencies of these two DMUs are equal. The main implication of Corollary 2.4 is the following: if we want to determine whether the efficiency rankings of two DMUs will reverse under certain parameter setting, it suffices to check the efficiency results given by two sets of lag parameters that can form a line segment in the parameter space containing the parameters of interest. So, if rank reversals occur (i.e., the ranks given by two different models are inconsistent), the closer the two sets of lag parameters are, the finer we can identify the exact lag parameters rendering two DMUs equally efficient. This property can be useful in determining changes in efficiency rankings in the multi-period lag model, and the condition can be checked without knowing the exact parameter values. Note that a change in the ranking is a stronger property than a change in efficiency scores and efficiency classification, in that the former implies the later.

We close this section by showing that, if a DMU is efficient under two different sets of lag parameters, this DMU will also be efficient under the convex combination of these two sets of lag parameters in $\Re_+^{J(m+1)}$.

Theorem 2.5. *Define Ω, Ω' and Ω'' as in Corollary 2.4. Then $\tilde{f}_i(\cdot, \Omega) = \tilde{f}_i(\cdot, \Omega') = 1$ implies that $\tilde{f}_i(\cdot, \Omega'') = 1$ for all $\lambda \in [0,1]$.*

Proof. Without loss of generality, suppose the production plans of all DMUs have been standardized by multiplying their input-output vectors with positive scalars, such that any DMU's input vector is not strictly larger or smaller than those of other DMUs. Recall that $\Omega = [\omega_q]_{q=1}^J$. Then by (2.11), it holds that $g_m([S_{kq}^{t_r}]_{r=a}^{a+m}, \lambda\omega_q + (1-\lambda)\omega_q') = \lambda g_m([S_{kq}^{t_r}]_{r=a}^{a+m}, \omega_q) + (1-\lambda) g_m([S_{kq}^{t_r}]_{r=a}^{a+m}, \omega_q') =$

$\lambda \sum_{r=0}^{m} \omega_q(r+1)S_{kq}^{t_{a+r}} + (1-\lambda) \sum_{r=0}^{m} \omega'_q(r+1)S_{kq}^{t_{a+r}}$, for all DMUs and all outputs q.

Since by hypothesis DMU-i is efficient under both ω and ω', it follows that $g_m([S_{iq}^{t_r}]_{r=a}^{a+m}, \omega_q) \geq g_m([S_{jq}^{t_r}]_{r=a}^{a+m}, \omega_q)$ and $g_m([S_{iq}^{t_r}]_{r=a}^{a+m}, \omega'_q) \geq g_m([S_{jq}^{t_r}]_{r=a}^{a+m}, \omega'_q)$, for any DMU-$j$ and all outputs q. By applying some algebra to these two inequalities, it yields $g_m([S_{iq}^{t_r}]_{r=a}^{a+m}, \omega''_q) \geq g_m([S_{jq}^{t_r}]_{r=a}^{a+m}, \omega''_q)$ for any DMU-j and all outputs q, which implies that DMU-i is efficient. Thus $\tilde{f}_i(\cdot, \Omega'') = 1$, and, since $\lambda \in [0,1]$ is arbitrary, we have completed the proof.

2.4 Estimating lagged productive effects

In the previous section, we introduced lagged effects, and formulated the dynamic DEA model used to measure efficiency in dynamic production. However, the computation of dynamic DEA models requires knowledge about the lag parameters $\mathbf{D}$ or Ω. Additional steps are therefore needed to determine the lag parameter values. This can be done in several ways. For instance, the information can be supplied by decision makers or external experts; we can also estimate the parameters from available input-output data. In this section, we elaborate on the latter suggestion.

Our estimation procedure consists of several steps: we first start by collecting the input-output data of interest, and then construct an econometric model and the associated impulse response structure to estimate lag parameters (see, e.g., Figure 2.3). Typically, the data used in the DEA model have a panel structure consisting of input and output information of different DMUs over some period of time. Therefore, the desired estimation method should be able to cope with multi-variate and dynamic panel structures. Vector autoregressive models (VAR) have been extensively applied to one DMU over time (e.g., Dekimpe and Hanssens, 1995, 1999). These models, however, do not deal with the panel structure associated with the dynamic DEA model (2.10).

In this chapter, we adopt the fixed effects PVAR model developed by Binder et al (2005). The PVAR model has attractive properties in providing consistent and asymptotically normal estimates regardless possible non-stationarity, unit roots or cointegration in the input or output series. We use PVAR to estimate the lag parameters in two steps. First, the PVAR estimation provides information about the dynamic interrelation among inputs and outputs. Next, the information is used to derive output responses due to shocks in inputs, which can be used as estimators of the lag parameters in (2.11). Figure 2.3 gives the general steps to implement our methodology.

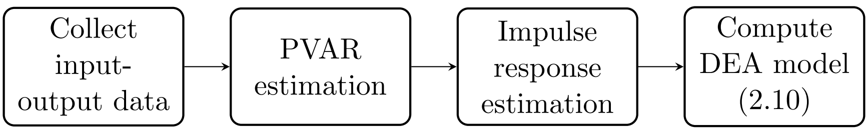


Fig. 2.3. Steps of the evaluative framework

In what follows, we briefly outline the relevant features of the PVAR model and the estimation procedure. Let $\tau = I + J$. The input-output variables can be jointly represented by an $\tau \times 1$ vector $\mathbf{y}_{kt} = [A_{k1}^t, \ldots, A_{kI}^t, S_{k1}^t, \ldots, S_{kJ}^t]$, for $t = 1, \ldots, n$, and $k = 1, \ldots, K$. The PVAR model is written as:

$$\mathbf{y}_{kt} = (\mathbf{I} - \boldsymbol{\Phi})\boldsymbol{\mu}_k + \boldsymbol{\Phi}\mathbf{y}_{k,t-1} + \boldsymbol{\epsilon}_{kt}, \quad \boldsymbol{\epsilon}_{kt} \sim iid(\mathbf{0}, \boldsymbol{\Lambda}_\epsilon). \tag{2.17}$$

In (2.17), the $\tau \times \tau$ matrix $\boldsymbol{\Phi} = [\phi_{ij}]$ defines the dynamic interrelations between inputs and outputs. These relations are assumed constant for the periods considered and independent of the DMUs. The $\boldsymbol{\mu}_k$ represent the fixed effects for the kth DMU, and $\boldsymbol{\epsilon}_{kt}$ white-noise disturbances.

For the purpose of estimation, the model is written in first differences:

$$\Delta\mathbf{y}_{kt} = \boldsymbol{\Phi}\Delta\mathbf{y}_{k,t-1} + \Delta\boldsymbol{\epsilon}_{kt}, \; t = 2, \ldots, n, \tag{2.18}$$

$$\Delta\mathbf{y}_{k1} = \boldsymbol{\kappa}_{k0} + \boldsymbol{\epsilon}_{k1}, \text{where } \boldsymbol{\kappa}_{k0} = -(\mathbf{I} - \boldsymbol{\Phi})(\mathbf{y}_{k1} - \mu_k). \tag{2.19}$$

The separate treatment of the first observation (2.19) is needed to deal with the incidental parameter problem induced by fixed short time series (Neyman and Scott, 1948). It involves the additional assumptions that $\boldsymbol{\kappa}_{k0}$ has zero mean and is independent of $\boldsymbol{\epsilon}_{k1}$ and $\Delta\boldsymbol{\epsilon}_{kt}$, for $t = 2, \ldots, n$.

Following Binder et al (2005), we apply the quasi-maximum-likelihood (QML) approach to estimate parameters of the PVAR model. Our QML implementation procedure is described in the appendix; please see Greene (2003) and Wooldridge (2002) for more extensive discussion about QML. In sum, the QML procedure yields estimates of $(2\tau \times \tau)$ unknown parameters of the $\boldsymbol{\Phi}$ and $\boldsymbol{\Lambda}_{\epsilon}$.

The calculation of lag parameters is based on the impulse response function associated with (2.17). Now we derive the impulse response pattern. Consider an initial impulse vector π_p from the pth input, the output responses in the rth period is given by the last J components of the vector $\mathbf{\Phi}^{r-1}\pi_p$. If the impulse response function is evaluated under the assumption that shocks occur independently of other input or output factors, then π_p has an one on the pth position and zeros elsewhere. However, when the observation periods are relatively long, the initial impulse may already have influenced outputs and other inputs within the initial period, in which case independence becomes an invalid assumption. Following Evans and Wells (1983), we take these concurrent shocks π_p into account by setting the initial impulse equal to pth column of $\mathbf{\Lambda}_{\epsilon}$ standardized on σ_{pp}, the corresponding diagonal element of the covariance matrix $\mathbf{\Sigma}$ of $\boldsymbol{\epsilon}_{kt}$. Figure 2.4 illustrates the impulse structure in the production process involving one input and one output. The associated lagged effect $D_p(\cdot, r)$ in the t_r period, $r = 1, \ldots, m+1$, may then be estimated as:

$$D_p(\cdot, r) = \text{the last } J \text{ components of the vector } (\mathbf{\Phi}^{r-1}\pi_p) \Big/ \sum_{r'=1}^{m+1} \mathbf{\Phi}^{r'-1}\pi_p, \quad (2.20)$$

where "/" denotes element-wise division between two vectors.

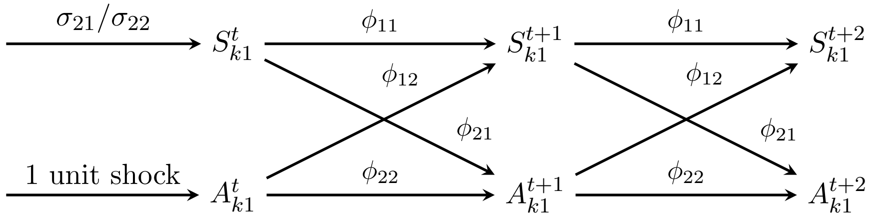


Fig. 2.4. Impulse response pattern for the one-period lag model assuming instantaneous shocks

Recall from the previous section that, to implement the output-oriented dynamic DEA (2.10), the parameters required to be estimated are the output-specific element of vector ω_q. This simplifying feature allows us to compute dynamic efficiencies from (2.10) with only the estimates of aggregate lagged effect about each output. Finally, we should also note that, since in VAR models the estimated lag parameters could have persistent effects (i.e., unit roots appear in $\mathbf{\Phi}$; see, e.g., Dekimpe and Hanssens, 1999), the choice of m has to be determined *a priori* by decision-makers based on their judgement about the production process.

In this section, we have shown how to use PVAR model to estimate lagged parameters in the dynamic DEA formulation. In the next section, we apply our methodology to the advertising-to-sales data of several major advertisers in North America to evaluate their advertising efficiencies; through this application, we will see the potential impact of static DEA models on the efficiency evaluation in dynamic situations.

2.5 Illustration: evaluating advertising efficiencies

According to TNS Media Intelligence, the total advertising spending of U.S. firms increases 4.2% in 2006 and comes to 148.71 billion dollars—an amount equivalent to 11.5 % of the national corporate profits of the year[2]. In spite of the astronom-

[2] Sources: http://www.tns-mi.com, and http://www.bea.gov.

ical amount of money invested in advertising, not every dollar invested provides the same value. Research has shown that more than half of the advertising expenditure fails to generate more sales (Abraham and Lodish, 1990). Given the amount of resources spent on advertising campaigns, firms that are efficient in advertising practices can attain a high level of competitive advantage, because they bear less costs in effectively delivering information to potential and attracted customers. However, not every dollar spent in advertising will end up with the same worth. Some firms are more efficient than the others, as they use less resource (advertising expenditures) to generate more outputs (sales). Therefore it is crucial that firms can benchmark their advertising performances with their competitors'. Based on the outcome of evaluation, firms can improve their performance by setting up benchmark targets and impose pressure on the incumbent media department or companies. Firms can also use this information to adjust their marketing strategies to the dynamic market situations.

We apply our methodology to real-world advertising data to demonstrate the impact of lagged effects on the DEA efficiency score. We consider the process of using advertising as a resource to generate sales. Although a firm's sales can be affected by other factors, such as the perceived quality of products, we consider advertising the most decisive factor behind consumer's purchase process and ignore others—this argument is supported by numerous marketing studies (e.g., Dekimpe and Hanssens, 1995, 1999; Färe et al, 2004; Rust et al, 2004; Luo and Donthu, 2005, 2006). Yet we should still note that advertising may help shape consumers' future perception of the product's quality (Nichols, 1998; Bagwell, 2007). The positive effect of the current advertising on future sales has been confirmed by numerous marketing studies (Clarke, 1976; Dekimpe and Hanssens, 1995, 1999). Using the annual advertising and sales data in the US auto-industry from 1970–94, Greuner et al (2000) find evidence that advertising Granger-causes profitability. Herrington and Dempsey (2005) similarly analyze the annual advertising and sales data of the auto-industry, and they show that marketing spending at different branch levels has nonidentical carry-over effect on future sales.

Although the effect of advertising on sales in general will depreciate within the range of 6 to 15 months (Clarke, 1976; Leone, 1995), we should note that our primary goal in this empirical example is to examine and show the difference in the evaluation results from the static and dynamic DEA models, as well as the bias caused by data intervals. Therefore we use the annual advertising to sales data; further, we will assume that firms in the sample are homogeneous in a competitive market, i.e., they face the same market condition, adopt the same intertemporal production technology in advertising, and the sales of one firm are not subject to the advertising of another firm.

2.5.1 Data and the model used

The panel data used span from 1997 to 2005, and include seven automobile producers and eight pharmaceutical companies from the top 100 North America advertisers list with complete data series in the *Ad e ı ı g Age* database (`http://adage.com`). The sample firms are selected because they have complete panel data over the sample period. The data collected cover annual sales and two types of annual advertising spending (media and paper). Table 2.1 summarizes the samples used in our application.

Table 2.1. Descriptive statistics of samples from two industries (in million US dollars)

	Automobile industry (n=7)			Pharmaceutical industry (n=8)		
	Media-based	Paper-based	Sales	Media-based	Paper-based	Sales
Mean	759.4	388.6	61590.8	352.8	131.2	13873.7
Std. dev.	449.5	286.5	41578.6	248.5	96.5	8376.1

We use the one-period lag DEA model with two inputs and one outputs ($m = 1$, $I = 2$, $J = 1$); we specify $m = 1$ (i.e., two productive periods) in view of the annual data considered. Lagged effects are estimated by PVAR for the two industries separately, so we can have a basis for comparison. In light of the limited panel dataset, we use the bi-variate PVAR model (i.e., sales versus paper and media advertising combined) to estimate lag parameters ω and assume that lagged effects are identical for firms in the same industry[3]. The bi-variate model has higher stability and parsimonity over the tri-variate model. The tri-variate model does not produce convergent estimates; this could be due to the limited sample size in the study.

2.5.2 Estimation results

For the automobile industry, the PVAR model yields

$$\hat{\mathbf{\Phi}} \approx \begin{bmatrix} 1.044 & 0.001 \\ 5.407 & 1.112 \end{bmatrix}, \ \hat{\mathbf{\Sigma}} \approx \begin{bmatrix} 0.039 & 0.292 \\ 0.292 & 40.559 \end{bmatrix}, \text{ and thus } \pi_1 \approx \left(1, \frac{0.292}{0.039}\right)'; \quad (2.21)$$

for the pharmaceutical industry, we have

$$\hat{\mathbf{\Phi}} \approx \begin{bmatrix} 1.058 & 0.001 \\ 1.149 & 0.822 \end{bmatrix}, \hat{\mathbf{\Sigma}} \approx \begin{bmatrix} 0.012 & 0.061 \\ 0.061 & 27.910 \end{bmatrix}, \text{ and thus } \pi_1 \approx \left(1, \frac{0.061}{0.011}\right)', \quad (2.22)$$

where $\hat{\mathbf{\Phi}}$ and $\hat{\mathbf{\Sigma}}$ are the estimates of $\mathbf{\Phi}$ and $\mathbf{\Sigma}$, respectively.

Based on the estimation outcomes (2.21) and (2.22), we can obtain the two-period accumulate sales response. For the auto-industry, the first period sales response is approximately equal to 13.662 dollars, which can be obtain from $\hat{\mathbf{\Phi}}\pi_1$ in (2.21). Therefore the total sales response due the a one-dollar shock in advertising expenses amounts to 21.083 dollars for the auto-industry. The accumulate sales response for pharmaceutical industries can be calculated similarly and is 10.629 dollars. Applying (2.20), the lag parameters for the automobile and pharmaceutical industry are $\omega_1(2) = 1 - (7.421/21.083) = 0.648$ and $\omega_1(2) = 1 - (5.202/10.628) = 0.510$, respectively. The outcomes suggest that in

[3] We should note again that the assumption is not required; users may specify firm- and time-specific estimation models when richer data are available.

the automobile industry 64.8% of the advertising effect extends beyond the current period into the next. In the pharmaceutical industry this percentage reaches 51.0%. The estimation results suggest strong lagged effects in the advertising process of both industries.

2.5.3 Results of DEA evaluations

Using these two estimated lagged effects, we apply our DEA model (2.10) to compute the dynamic efficiencies of all sampled companies. The results for firms in the two industries are displayed in Figures 2.5 and 2.6. These figures also show the corresponding efficiencies obtained from the static DEA model (2.5) in the eight-year period. The annotated numbers in the figures indicate the rankings of firms in a particular year. Note that we have trimmed 2005 from the evaluation result due to the two-period lag structure considered.

We should note that rank reversals and inaccurate efficiency estimates can dramatically influence a firm's subsequent marketing decisions. The evaluation results indicate that dynamic effect can significantly affect the efficiency assessment. Applying the Wilcoxon signed-ranks test to paired efficiency results of firms, we find a significant discrepancy between the scores obtained from the dynamic and static DEA models for firms in the automobile industry at the 5% significance level ($p < 1\%$). For the pharmaceutical industry, however, we maintain the null hypothesis that two efficiency scores come from the same population ($p = 0.3616$). So even under the assumption on the lag structure the was made earlier, we can still observe a marked impact on the evaluation results due to the dynamic effects in production.

The hypothesis tests reveal mixed results that some firms or industries are more susceptible to lagged effects than others. In particular, firms in the automobile industry experience additional ranking changes when the lagged effect is considered (i.e., 3.29 reversals per firm versus 1.38 reversals per firm in the pharmaceutical industry). The difference can be attributed to the disparity in the intensity of lagged effects. Another reason for the distinction might be that the

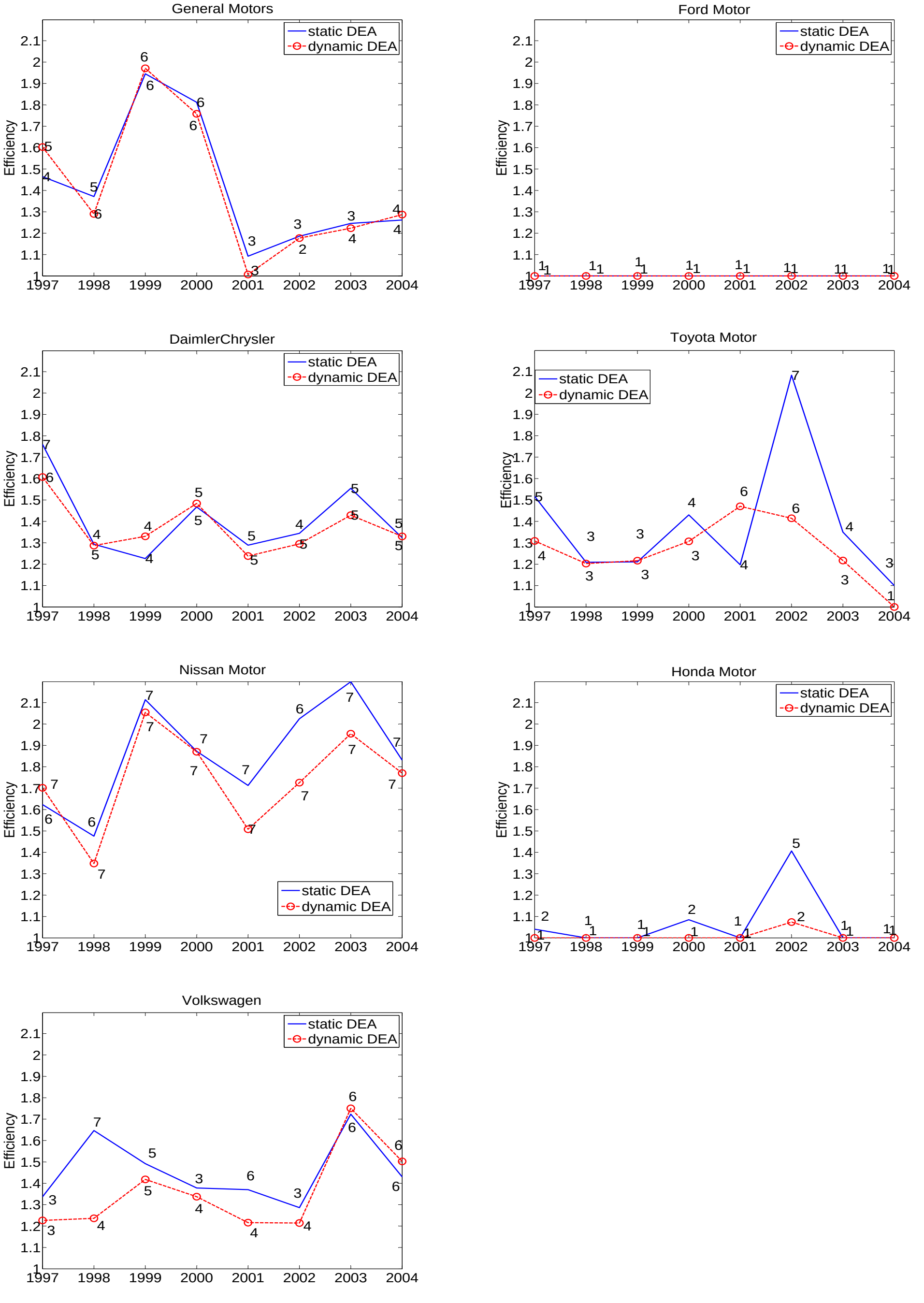


Fig. 2.5. Efficiencies from the static and dynamic DEA models (automobile industry)

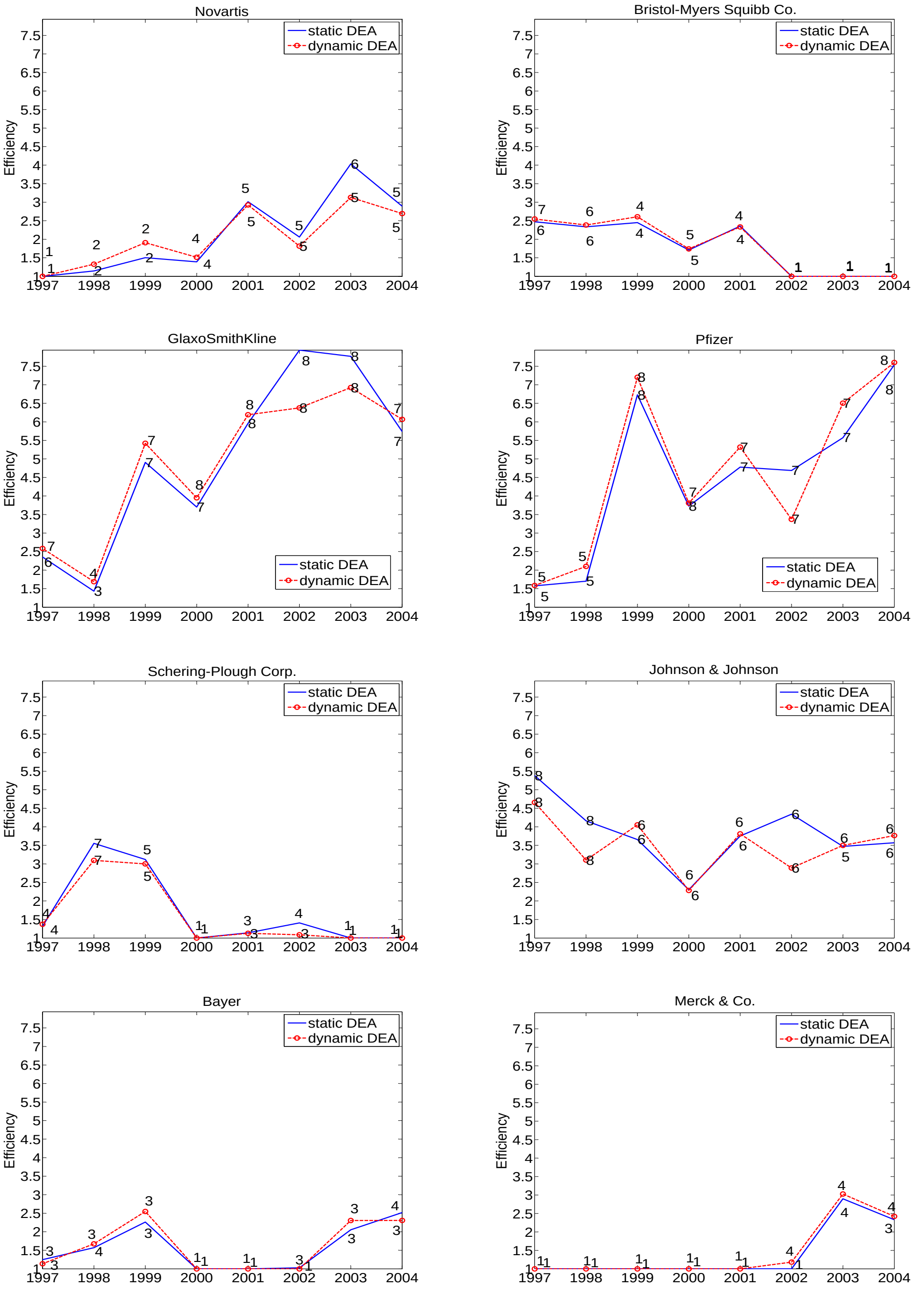


Fig. 2.6. Efficiencies from the static and dynamic DEA models (pharmaceutical industry)

sampled pharmaceutical firms all exhibit a "trendwise" production pattern over the observation periods, so that the difference between the dynamic and static DEA formulations are not as evident as the lag parameter estimates suggest (c.f. Theorem 2.1). By inspecting efficiency scores of all firms in individual industries, we can observe that static DEA models tend to overestimate the efficiency score of firms in the automobile industry. In the pharmaceutical industry, scores obtained from two models are not significantly different.

As for the efficiency changes, nearly all DMUs experience changes in their efficiency scores under lag effects (with an exception for Ford being the all-time efficient advertiser[4]), although rank reversals do not occur in all situations. These changes also imply that the frontier, or the relative positions of DMUs with respect to the frontier, alters with different values of dynamic parameters. Moreover, lagged effects have changed the observed efficiency status for certain DMUs; for example, see Honda in 1997 and 2000, Toyota in 2004, Bayer in 2005, and Merk. & Co. in 2002. Yet, differences between two models are not always in the same direction. More specifically, the dynamic efficiencies relate to production over two periods, and therefore they are not consistently produce scores higher or lower than the results from the static DEA—this condition is a contrast to the situation shown in Theorem 2.5.

To sum up, our results show that lagged effects can lead to substantial discrepancies in evaluation results. Biased evaluation results would easily lead to erroneous decision and policy making for the firm. Therefore we should always take a broader perspective in evaluating longitudinal performance by incorporating the effects into evaluation and decision-making processes.

2.6 Concluding remarks and suggestions

In this chapter we have developed an integrated methodology to incorporate lagged effects of input consumption into the DEA efficiency measurement. In

[4] Unfortunately we could not find the media coverage supporting Ford's efficiency status.

particular, we have formulated lagged effects via parametric programming, and the resultant formulation is a generalization of the static DEA model. Moreover, our methodology integrates the dynamic DEA formulation with the PVAR estimation technique to systematically estimate the dynamic parameters. The proposed methodology is illustrated with an application to advertising efficiencies of top advertisers from the automobile and pharmaceutical industry in North America. The results demonstrate that lagged effects can lead to changes in efficiency scores, rankings, and efficiency classification. So, using static DEA models in dynamic production can be potentially misleading. As many production situations involve substantial dynamics, our methodology can be applied to a wide range of evaluation problems in place of conventional DEA models, and therefore provides further insights into firms' dynamic performance.

Like the advertising process illustrated in this chapter, many aspects of supply chain operations are also subject to the self-reinforcing dynamic impact; for instance, miscellaneous capital and human resource investments, supplier relationships, and building brand loyalty. The key message in this chapter is that managers should be mindful of the influence of dynamic effects, because it usually seems dormant but could lead to significant changes to the evaluation results.

In the next Chapter, we will extend the dynamic DEA model introduced in this chapter to production networks, which are made of interconnected production units. We will develop a system of efficiency measures for dynamic production networks, and explore various theoretical properties underlying the efficiency measures.

Appendix: the QML estimation procedure

The likelihood function is based on the joint distribution of $\varDelta\mathbf{y}_k = (\varDelta\mathbf{y}'_{k1}, \varDelta\mathbf{y}'_{k2}, \ldots, \varDelta\mathbf{y}'_{kn})'$. Then the estimation can be accomplished in two steps:

1. Using (2.18) and (2.19), this column vector can be conveniently rewritten as $\varDelta\mathbf{y}_k = \mathbf{R}^{-1}\varDelta\boldsymbol{\eta}_k$, with $\varDelta\boldsymbol{\eta}_k = (\boldsymbol{\epsilon}'_{k1}, \varDelta\boldsymbol{\epsilon}'_{k2}, \ldots, \varDelta\boldsymbol{\epsilon}'_{kn})'$ and $\mathbf{R}$ a non-singular linear transformation matrix. This $\varDelta\boldsymbol{\eta}_k$ has mean zero and a constant, block tri-diagonal covariance matrix $\boldsymbol{\Sigma}_{\varDelta\boldsymbol{\eta}}$.
2. Denote $\tilde{\boldsymbol{\Psi}} = E(\mathbf{y}_{kt} - \boldsymbol{\mu}_k)(\mathbf{y}_{kt} - \boldsymbol{\mu}_k)'$, which is a symmetric positive definite matrix. The main diagonal blocks of $\boldsymbol{\Sigma}_{\varDelta\boldsymbol{\eta}}$ are then equal to $E(\varDelta\boldsymbol{\epsilon}_{k1}\varDelta\boldsymbol{\epsilon}'_{k1}) = (\mathbf{I} - \boldsymbol{\Phi})\tilde{\boldsymbol{\Psi}}(\mathbf{I} - \boldsymbol{\Phi}) + \boldsymbol{\Lambda}_\epsilon$, and $E(\varDelta\boldsymbol{\epsilon}_{kt}\varDelta\boldsymbol{\epsilon}'_{kt}) = 2\boldsymbol{\Lambda}_\epsilon$ for $t = 2, \ldots, n$. The blocks on the two parallel diagonals are equal to $E(\varDelta\boldsymbol{\epsilon}_{kt}\varDelta\boldsymbol{\epsilon}'_{k,t-1}) = -\boldsymbol{\Lambda}_\epsilon$, for $t = 2, \ldots, n$. Consequently, $\varDelta\mathbf{y}_k$ has mean zero and a covariance matrix $E(\varDelta\mathbf{y}_k\varDelta\mathbf{y}'_k) = \mathbf{R}^{-1}\boldsymbol{\Sigma}_{\varDelta\boldsymbol{\eta}}\mathbf{R}^{-1'}$. Let $\boldsymbol{\Psi} = E(\varDelta\boldsymbol{\epsilon}_{k1}\varDelta\boldsymbol{\epsilon}'_{k1})$.

3

Measuring the dynamic performance of supply networks

In Chapter 2, we introduce the dynamic DEA model for individual production units—the dynamic effect impacts the same unit over time. We have shown that the evaluation results can be biased if the evaluator does not consider these effects in efficiency measurement. However, if we are given explicit information of the internal sub-processes, the dynamic effect discussed in the previous chapter (i.e, self-loop effect) can be more explicitly represented as the dynamic productive interrelations among different sub-processes in the network.

In this chapter, we will show that tapping into the internal processes can reveal more inefficient areas for further improvement; we also develop a system of new efficiency indexes to capture the dynamic effects among sub-processes, and to unify different units to maximize the network's efficiency in terms of the evaluation results. Through the network model we want to answer the following questions: how to systematically measure the production efficiency of a network, as well as its sub-processes in the presence of internal dynamic effects? how can we trace the inefficiency of the network back to its source "in" the network? what is the relation between our dynamic network approach and the traditional DEA efficiency measures? Answering these questions can help managers work toward improved network performance in dynamic production, which is the goal of the current chapter.

The model of dynamic production networks is built upon the principles developed in Chapter 2. More specifically, we propose a network-DEA model to systematically cope with the dynamic effect within a production network. Various interconnections between the new measure and the DEA efficiency have also been established. We also formalize the relationship between returns-to-scale properties of decision-making units (DMU)s and those of its constituting Sub-DMUs (SDMUs). The network DEA model presents a unified framework to analyze performances in a dynamic production network.

3.1 Introduction

As noted in Chapter 2, Data envelopment analysis (DEA) has proved to be a useful tool in evaluating relative performance of homogeneous (DMUs) in a multiple-input multiple-output setting. Generally, DEA estimates the efficiency index by calculating the ratio of weighted outputs to weighted inputs, and the input and output weights are decided according to the best interests of the DMU being evaluated. This flexible weighting scheme relaxes the requirement of a priori value judgments for computing the efficiency score. Therefore, based on input and output quantities, DEA can still assess the efficiency of DMUs, even when the information regarding prices and production processes is difficult to obtain or unavailable. However, by resorting merely to DMU-level input and output data, DEA treats the production process as a black box, meaning that it imposes a few assumptions on the internal transformation processes (see, e.g., Banker, 1993). Consequently, knowledge of the internal activities of a DMU is not utilized in the analysis, and insights about how to improve the performance of the DMU from within become largely obscure (see also Homburg, 2001).

Several studies attempt to tackle this issue by adopting an explicit representation of the production processes inside a DMU (e.g., Yang et al, 2000; Castelli et al, 2001, 2004; Lewis and Sexton, 2004). In these studies, the interdependence between different sub decision-making units (SDMUs) is represented by an intra-connected production network, in which SDMUs consume inputs (which can be either exogenous inputs or intermediate outputs produced by other SDMUs) to yield outputs (which can be either intermediate outputs or final outputs that will depart the DMU). These underlying interrelationships among SDMUs are often masked by the ordinary DEA methodology. These studies, however, still ignore an important fact that the production processes of DMUs and SDMUs often have a temporal dimension, and without considering this dimension it would easily lead to distorted efficiency measurement. In particular, intermediate outputs used by one SDMU today may potentially influence its levels of outputs in the future. One straightforward example is the use of inventory. Other common examples include (1) capital accumulation (Emrouznejad and Thanassoulis, 2005), (2) the use of fertilizer in agriculture and the effect of pollution in the environmental context, and (3) various managerial activities used to improve organizational performance, such as the investment in advertising (Clarke, 1976) and the implementation of a new human-resource strategy (Huselid and Becker, 1996). In some situations, the intermediate output can even have a negative short-term influence on production (see, e.g., De Meyer and Ferdows, 1990; Cooper et al, 2004).

Färe et al (1996) introduce the formulation of storable inputs to allow asynchronism between the appearance of inputs and the use of inputs in the dynamic production model. While their approach considers dynamics of production, Färe and Grosskopf, instead of adopting a broader network perspective, confine their analysis to the dynamics of a single production process linked over multiple time periods. In their study, the intertemporal effect is limited to inputs only, and the perishability of storable inputs is not considered. Moreover, the emphases of Färe et al (1996) and other recent studies concerning quasi-fixed inputs within the dynamic framework (e.g., Nemoto and Goto, 2003; Ouellette and Vierstraete, 2004) center primarily on the efficient allocation or adjustment of inputs over time. The literature does not provide a clear guideline as for how to incorporate dynamic effects in production networks into efficiency measurement—these effects have been largely neglected or assumed to be nonexistent, say, by imposing balancing constraints on the network production model (e.g., Castelli et al, 2004). Therefore the impact of dynamic effects on efficiencies remains unclear and still requires formal and systematic treatment.

To tackle these issues, we develop a unified framework to analyze the performance of a dynamic production network. We achieve this by first analytically stratifying the structure of production networks according to the production characteristics of SDMUs. The intent is to develop a systematic view on the structure of production networks, so as to facilitate legitimate comparisons among the production units in different stratifications in the network. We then introduce a new efficiency measure to assess the performance of different hierarchical levels in the dynamic production system. Our efficiency measure can be decomposed in a way similar to the approach used to analyze the structure of the network. The output of the analysis can provide specific recommendations to decision-makers of different concerns and orientations. Also, we show that the new measure has a close connection with the conventional DEA-efficiencies, in either case with or without considering the internal structure of DMUs. This finding can assist decision-makers with clear positioning and a strategic direction in the course of performance improvement. Lastly, we also investigate the relationship between the returns-to-scale properties of DMUs and those of its constituting SDMUs. This result is crucial to determining the minimum input requirement in the general network production model. Revealing this linkage also sheds new light on how a DMU can improve its scale performance from within.

This chapter will unfold as follows. In Section 2 we introduce the basic DEA formulation and an analytic approach to describing dynamic production networks. We also provide a simple example to illustrate that using conventional DEA models in a dynamic production environment would lead to biased results. In Section 3 we develop the new efficiency measure. In Section 4 we discuss some returns-to-scale properties of production networks. An application of the model to a numerical example is presented in Section 5. Section 6 provides the conclusion.

3.2 Network DEA models

To lay the groundwork for subsequent discussions, we give a brief introduction to the conventional DEA in this section. In this model the production processes within a DMU are treated as a black box (i.e., we are only concerned about the input/output quantities on the DMU level). With that in mind, we then present the concept and representation of production networks and dynamic effects.

3.2.1 Conventional DEA-efficiency

Consider a set of DMUs indexed by $\mathbf{K}$, operating at a particular time period t_m within the observation window indexed by T. For all $k \in \mathbf{K}$, DMU$_k$ uses inputs $x_k^{t_m} = [x_{pk}^{t_m}]_{p=1}^{|P|} \in \Re_+^{|P|}$ to produce outputs $z_k^{t_m} = [z_{uk}^{t_m}]_{u=1}^{|U|} \in \Re_+^{|U|}$, where P and U are respectively the index sets for inputs and outputs, and $\Re_+^*$ represents the *-dimensional semipositive real space. For the time being, all inputs used are assumed to have a *contemporaneous correspondence* to outputs, meaning that inputs contribute only to the production in the same time period and vice versa. The input-oriented technical efficiency of DMU$_0$ can be measured by the CCR model below (Charnes et al, 1978):

$$
\begin{aligned}
&f_{CCR}\big((x_0^{t_m}, z_0^{t_m})|(x_k^{t_m}, z_k^{t_m})\forall k \in \mathbf{K}\big) = (\tilde{\vartheta}_0^{t_m}, \tilde{\lambda}_0, \tilde{s}_{P0}^{t_m-}, \tilde{s}_{U0}^{t_m+}) \\
&\quad = \operatorname{argmin}\Bigg\{\vartheta_0^{t_m} - \epsilon(\sum_{p\in P} s_p^{t_m-} + \sum_{u\in U} s_u^{t_m-})\Bigg| \\
&\qquad \sum_{k\in\mathbf{K}} \lambda_k x_{pk}^{t_m} + s_{p0}^{t_m-} = \vartheta_0^{t_m} x_{p0}^{t_m} \ \forall p \in P, \\
&\qquad \sum_{k\in\mathbf{K}} \lambda_k z_{uk}^{t_m} - s_{u0}^{t_m+} = z_{u0}^{t_m} \ \forall u \in U, \\
&\qquad \lambda_k, s_{p0}^{t_m+}, s_{u0}^{t_m+} \text{ are nonnegative real numbers}\Bigg\}, \\
&\text{where } \tilde{\lambda}_0 = [\lambda_k]_{k=1}^{|\mathbf{K}|}, \tilde{s}_{P0}^{t_m-} = [\tilde{s}_{p0}^{t_m-}]_{p=1}^{|P|}, \tilde{s}_{U0}^{t_m+} = [\tilde{s}_{u0}^{t_m+}]_{u=1}^{|U|}, \\
&\epsilon \text{ is a small positive number.}
\end{aligned}
\tag{3.1}
$$

The first argument of the optimal set mapping f_{CCR} is the input-output ordered pair of DMU_0. The second argument, namely $(x_k^{t_m}, z_k^{t_m})$ $\forall k \in \mathbf{K}$, represents the collection of all input/output data used to construct the referenced technology with which DMU_0 is compared. The objective of the LP in (3.1) is to proportionally minimize the input vector of DMU_0 and simultaneously maximize possible input and output slacks, provided that the output vector is feasible in the program. In particular, denoting the optimal solution of LP (3.1) by $(\tilde{\vartheta}_0^{t_m}, \tilde{\lambda}_0, \tilde{s}_{P0}^{t_m-}, \tilde{s}_{U0}^{t_m+})$, it can be shown that $\tilde{\vartheta}_0^{t_m} \in (0, 1]$, and $\tilde{\vartheta}_0^{t_m} x_0^{t_m} - \tilde{s}_{P0}^{t_m-}$ represents the minimal input consumption while $z_0^{t_m} + \tilde{s}_{U0}^{t_m+}$ is still producible. Then DMU_0 is called *weakly efficient* if $\tilde{\vartheta}_0^{t_m} = 1$, and *CCR-efficient* if it is weakly efficient and the slack vectors $\tilde{s}_{P0}^{t_m-}, \tilde{s}_{U0}^{t_m+}$ are componentwise zero. Note that *CCR-efficiency* is by definition a stronger property than *weakly efficient*. Assumption on variable returns-to-scale (VRS) technology can be implemented by appending one additional constraint such that λ_k's sum up to one (see Banker and Thrall (1992) for discussions on returns-to-scale in DEA). To make a clear distinction, the result obtained from LP (3.1) is henceforth referred to as "DEA-efficiencies".

3.2.2 Motivational example

We provide an example in this section to exemplify that conventional DEA and network DEA models in the literature can break down in the presence of dynamic effects. In this example, we measure the efficiency of three supply chains (DMUs), each consisting of a manufacturing plant (Mfg) and a distribution center (DC) to perform production activities (see Figure 3.1). The input, output, inventory quantities (inv.), and efficiency scores are shown in Table 3.1. Particularly, in Column 4 the italic figures in the parentheses represent the level of intermediate outputs that links to final outputs produced in the same period; Column 5 displays the inventory level of DCs. For example, the Mfg-a uses 8 units of input to produce 5 units of intermediate product in time period t_0; the corresponding DC receives the intermediate outputs and processes it with its labor input to produce 6 units of final output. For the moment we suppose all DCs use labor in proportion to the level of intermediate outputs used. So its effect can be neglected, and we can focus on the dynamic effect of intermediate outputs. More specifically, in t_0 DC-a and DC-c actually used 3 units and 4 units of the intermediate outputs, so in t_0 2 units of intermediate outputs were inventoried in DC-a, 1 unit for DC-c, and none for DC-b. These inventoried intermediate outputs are then used to produce DC's outputs in t_1, and for the moment the quality of the inventory are assumed to remain constant over time (i.e., one unit of input stored in this period can be used equivalently as one unit of input in the next period). Thus only DCs are susceptible to the dynamic effect.

The Mfgs (DCs) of these three supply chains are benchmarked with Mfgs (DCs) of the same period. The figures in the parentheses of Column 3, 8 and 9 give the ranks of the efficiency scores. When dynamic effects are considered in the analysis, all DCs are CCR-efficient in time period t_0 and t_1 (Column 7). Given the fact that all DCs are actually CCR-efficient, the operation of Mfg should be the only source of inefficiency and therefore the supply chains' efficiency ranking should follow those of Mfgs (Column 3). However, the rankings obtained from the CCR model (Column 8) and the model of Lewis and Sexton (2004) (Column

Table 3.1. Data and evaluation results of the supply chain example

Column#	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
DMU	x_m	y_m	eff_m	y_m	inv.	z_{dc}	eff_{dc}[1]	eff_{DMU}[2]	eff_{DMU}[3]
$(t_0)a$	8	5	1.00(1)	5(*3*)	2	6	1.00	0.75(2)	0.60(2)
b	10	5	0.80(2)	5(*5*)	0	10	1.00	1.00(1)	0.80(1)
c	12	5	0.67(3)	5(*4*)	1	8	1.00	0.67(3)	0.53(3)
$(t_1)a$	12	5	0.67(3)	5(*7*)	0	14	1.00	0.78(2)	0.67(2)
b	10	5	0.80(2)	5(*5*)	0	10	1.00	0.67(3)	0.57(3)
c	8	5	1.00(1)	5(*6*)	0	12	1.00	1.00(1)	0.85(1)

[1] DC's real efficiency.
[2] DMU's efficiency scores given by the CCR DEA model.
[3] DMU's efficiency scores given by the index from Lewis and Sexton (2004).

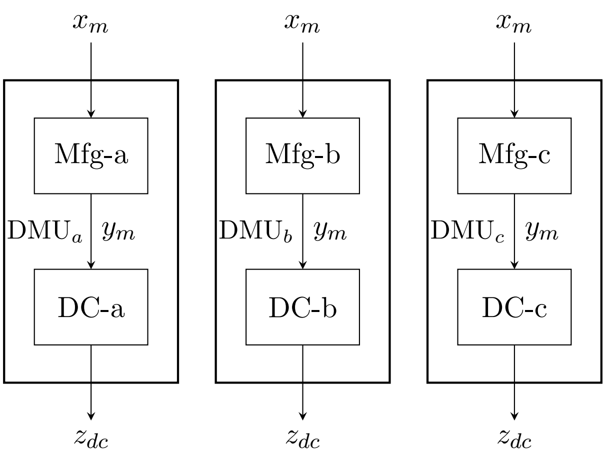


Fig. 3.1. Illustration of the supply chain example

9) deviate from the anticipated results in both t_0 and t_1, indicating that these two models can produce misleading results when dynamic effects exist.

3.2.3 Production networks

We now formally introduce the analysis of production networks. Consider the case where two SDMUs I_1 and J_1 are found in DMU_k $\forall k \in \mathbf{K}$ (see Figure 3.2). Then, in the case of no dynamic effect, the input/output vectors related to DMU_k can be recast as $x_k^{t_m} = [x_{I_1k}^{t_m}\ x_{J_1k}^{t_m}]$ and $z_k^{t_m} = [z_{J_1k}^{t_m}]$, where $x_{I_1k}^{t_m} \in \Re_+^{|P_I|}$ and $x_{J_1k}^{t_m} \in \Re_+^{|P_J|}$ are the external inputs used by I_1 and J_1 in time period t_m, respectively. Clearly $|P_I| + |P_J| = |P|$. In particular, SDMU I_1 uses $x_{I_1k}^{t_m}$ to produce intermediate outputs $y_{I_1J_1k}^{t_m} \in \Re_+^{|Q|}$, where the subscripts specify the origin I_1 and the destination J_1 of the intermediate outputs indexed by Q. The intermediate outputs can be alternatively expressed as a vector $[y_{qI_1J_1k}^{t_m}]_{q=1}^{|Q|}$. SDMU J_1 employs both $x_{J_1k}^{t_m}$ and $y_{I_1J_1k}^{t_m}$ produced by I_1 to yield the final outputs $z_{J_1k}^{t_m}$. Thus we can define the homogeneity of SDMUs as:

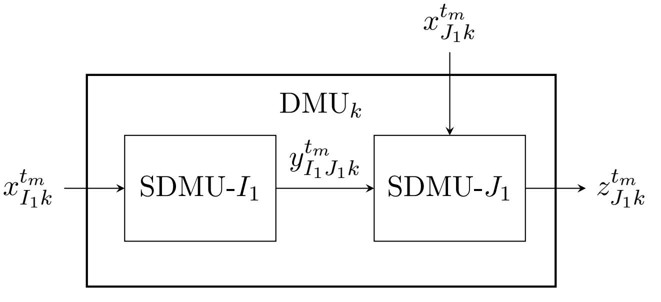


Fig. 3.2. Production networks (no dynamic effect)

Definition 3.1 (Homogeneous SDMUs). *Two SDMUs I_1 and I_2 are homogeneous if and only if they employ the same inputs to produce the same outputs. Two SDMUs belong to the same tier if they are homogeneous.*

By Definition 3.1, the membership of a tier‘ is actually defined in terms of the homogeneity of SDMUs. Consequently, homogenous SDMUs can measure their relative efficiencies by making use of LP (3.1) with all other SDMUs in the same tier being the reference group. Moreover I_1 and J_1 can only be compared with their counterparts in their own tiers according to this definition.

Tiers in a DMU

We continue to extend the concept to the case where individual tiers within one DMU consist of multiple SDMUs. Then the environment described in the preceding subsection becomes a special case. However we should note that, by treating individual tiers in the multi-SDMU model as black boxes, we again return to the single-SDMU model. Now consider the case where there are two tiers I and J in each DMU (i.e., two distinct groups of homogeneous SDMUs). SDMUs in these two tiers in DMU_k can be represented by the non-empty tier sets $\mathcal{L}_I^k$ and $\mathcal{L}_J^k$, respectively. Further we denote two universal tier sets by $\mathcal{L}_I$ and $\mathcal{L}_J$, where $\mathcal{L}_I = \bigcup_{k\in\mathbf{K}} \mathcal{L}_I^k$ and $\mathcal{L}_J = \bigcup_{k\in\mathbf{K}} \mathcal{L}_J^k$. After defining these notations, we can analytically describe each DMU_k in terms of its constituent SDMUs: $(\mathcal{L}_I^k, \mathcal{L}_J^k, \mathcal{A}^k)$, where $\mathcal{L}_I^k \subseteq \mathcal{L}_I$ and $\mathcal{L}_J^k \subseteq \mathcal{L}_J$ and $\mathcal{A}^k$ denotes the arc set of DMU_k. The arc set represents the connectivities between SDMUs in one tier to those in the other. More generally, we can describe the production process of an arbitrary DMU_k comprising a total of l tiers, as an ordered $(l+1)$-tuples $(\mathcal{L}_1^k, \mathcal{L}_2^k, \ldots, \mathcal{L}_l^k, \mathcal{A}^k)$.

Furthermore, let $\mathcal{S}^k$ denote the collection of all SDMUs in DMU_k, then $\bigcup_{i=1}^{l} \mathcal{L}_i^k = \mathcal{S}^k$, and $\mathcal{L}_{l_1}^k \bigcap \mathcal{L}_{l_2}^k = \varnothing$ for any $l_1, l_2 \in l$, $l_1 \neq l_2$. These expressions imply that each SDMU can belong to one tier only, and each DMU has at least one SDMU in each tier. To remain logical, we also assume SDMUs do not consume intermediate outputs from SDMUs in the same tier, and therefore SDMUs within each tier are not interconnected (i.e., serial production networks). We are ready to define the structural homogeneity of DMUs that have multiple tiers of SDMUs:

Definition 3.2 (Structurally homogeneous DMUs). *DMU-k_1 and DMU-k_2 are structurally homogeneous if, and only if $\mathcal{A}^{k_1} = \mathcal{A}^{k_2}$ and $n(\mathcal{L}_l^{k_1}) = n(\mathcal{L}_l^{k_2})$ for all l, where $n(\cdot)$ is equal to the cardinality of the set.*

Definition 3.2 defines the homogeneity of DMUs in terms of their tier structure. Similar to the homogeneity notion in conventional DEA, Definition 3.2 determines which DMUs are amenable to the analysis of our model. Also, it is clear that structural homogeneity implies the homogeneity in the conventional DEA models but the reverse does not necessarily hold. In conclusion, we show that production networks can be characterized by the structural relationship between different hierarchical production units: a DMU's operation comprises the flows from and between the exterior and its internal tiers, and the the tiers' production activities are fulfilled by their subordinate SDMUs.

3.2.4 Dynamic effects in the duo-tier network

Following the illustrative example just given, we introduce the analysis to the dynamic effect in a duo-tier production network. To facilitate the presentation, later discussions will be limited to the single-SDMU model, which is shown in Figure 3.3-a and Figure 3.4. Nevertheless, the concept used to construct the single-SDMU model (hereafter "the model") is equally applicable in the extended multi-SDMU model (see Figure 3.3-b). In the model, dynamic effects prevail only in the tier $\mathfrak{L}_J$ and are represented by the shaded triangle in Figure 3.3 and Figure 3.4. The notations used here follow those introduced in the preceding subsections. So in $t_m \in T$, DMU$_k$ uses $x_k^{t_m} = [x_{I_1k}^{t_m}\ x_{J_1k}^{t_m}]$ to produce $z_k^{t_m} = [z_{J_1k}^{t_m}]$. Specifically, if we denote the i-th SDMU in tier I of DMU$_k$ by $s(i, I, k)$, then $s(1, I, k)$ consumes $x_{I_1k}^{t_m}$ to produce the intermediate output $y_{I_1J_1k}^{t_m}$, and $s(1, J, k)$ employs both $y_{I_1J_1k}^{t_m}$ and $x_{J_1k}^{t_m}$ to yield $z_{J_1k}^{t_m}$.

As for the dynamic factors, we define $\alpha_{I_1J_1k}^{t_mt_n} = [\alpha_{qI_1J_1k}^{t_mt_n}]_{q=1}^{|Q|}$ where $\alpha_{qI_1J_1k}^{t_mt_n} \in [0, 1]\ \forall q \in Q$. For DMU$_k$, each component in this vector specifies the proportion of an intermediate output q that was produced by $s(1, I, k)$ in t_m, received by $s(1, J, k)$ and takes effect in t_n. The effectiveness of the *unconsumed* intermediate output is contingent on the factor $\beta^{t_mt_n} = [\beta_q^{t_mt_n}]_{q=1}^{|Q|}$, where $\beta_q^{t_mt_n} \geq 0\ \forall q \in Q$. The value of this factor will depend on the operational environment. This factor can readily express the degree of perishableness of intermediate outputs when the value is strictly less than one. We can further assume that (i) the dynamic effects influence the target periods only, and these effects will be fully exploited in the the target periods (i.e, no compound effect exists), and (ii) the system does not

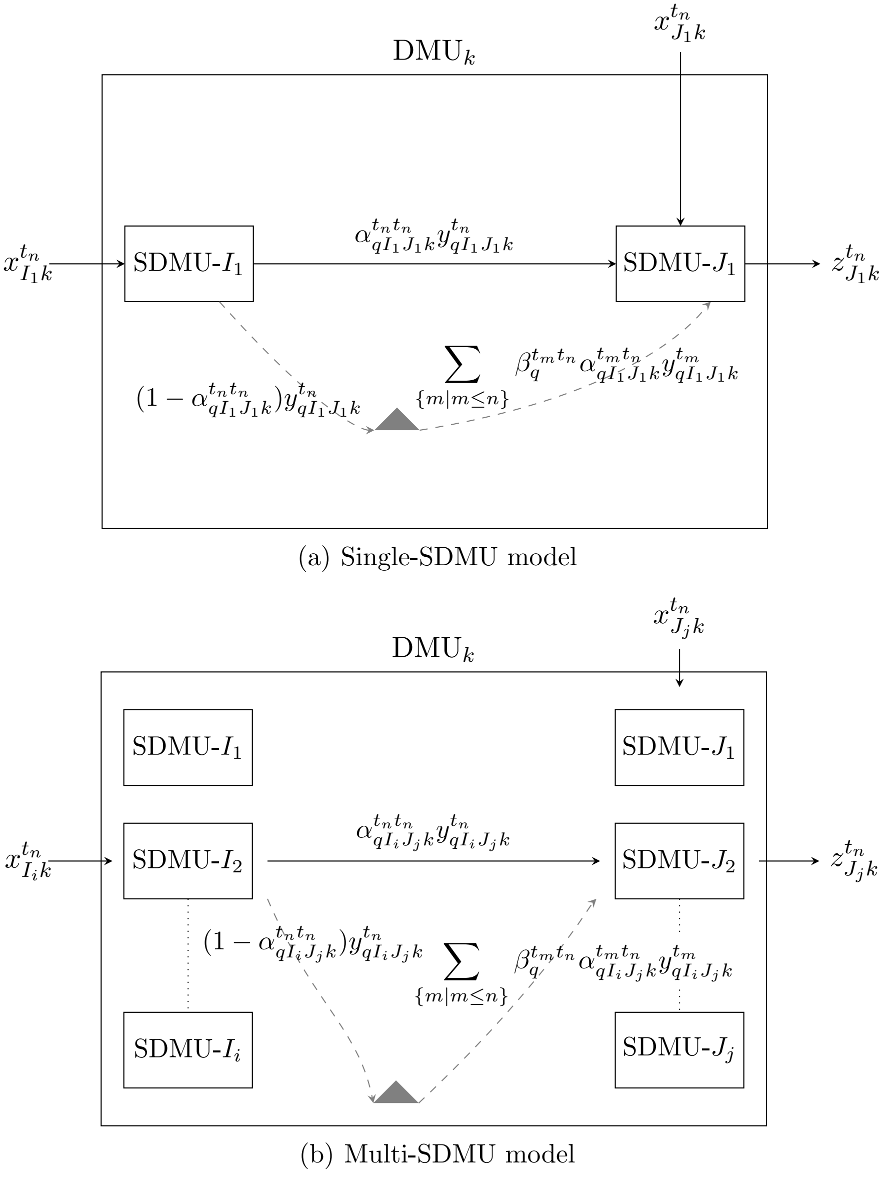


Fig. 3.3. Single-SDMU and Multi-SDMU model (cross-section view)

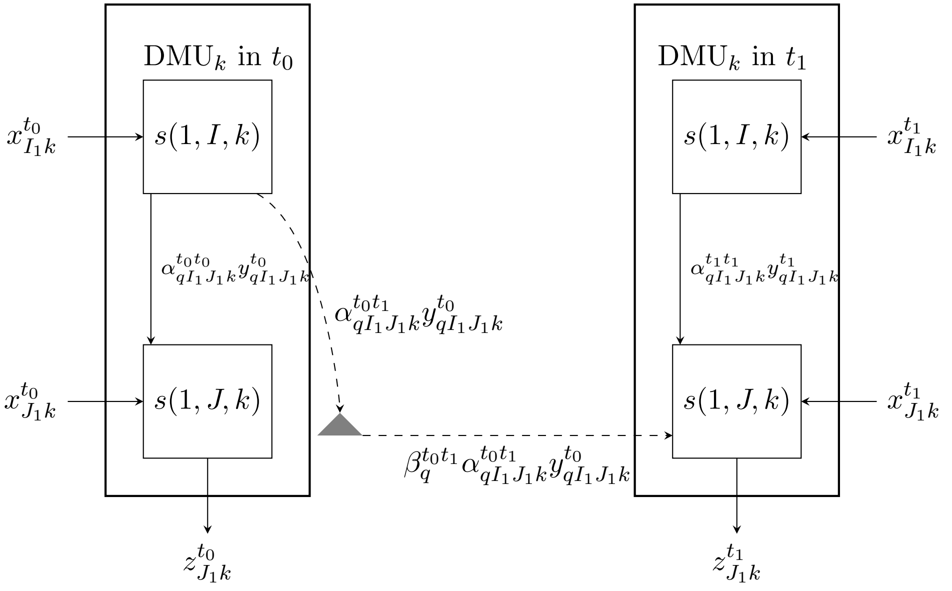


Fig. 3.4. Dynamic structure of the single-SDMU Model

produce residual dynamic effect affecting the production in all subsequent periods beyond the observation window T (see, e.g., Figure 3.4). Then by definition it follows that:

$$\sum_{\{n|n\geq m;t_m,t_n\in T\}} \alpha^{t_mt_n}_{qI_1J_1k} = 1 \ \forall t_m \in T, q \in Q, k \in \mathbf{K} \tag{3.2}$$

Note that zero is not a permissible value for $\alpha^{t_mt_n}_{qI_1J_1k}$ when $t_m = t_n = t_0$ (i.e., the first period of production), since in this case the model would violate the production axiom—null inputs produce non-zero outputs in the first period t_0 of production (see, e.g., Färe et al (1996), p. 12). Similarly it also follows that $\beta^{t_mt_n}$ is a non-zero vector. Then the effective intermediate outputs used by $s(1,J,k)$ in t_n for production are (see also Figure 3.3):

$$\alpha_{qI_1J_1k}^{t_nt_n} y_{qI_1J_1k}^{t_n} + \sum_{\{m|m\leq n, t_m, t_n \in T\}} \beta_q^{t_mt_n} \alpha_{qI_1J_1k}^{t_mt_n} y_{qI_1J_1k}^{t_m} \ \forall q \in Q \tag{3.3}$$

To neatly demonstrate the core ideas of the proposed model, this chapter focuses on the efficiency measuring in the two-period case, i.e., $T = \{t_0, t_1\}$. In this setting, the dynamic effects only influence the adjacent time period. Formally, this means $\alpha_{I_1J_1k}^{t_mt_n} = 0$ for all $\{t_m, t_n \in T | t_n - t_m > 1\}$ and $k \in \mathbf{K}$. As can be seen in Figure 3.4, only $\alpha_{I_1J_1k}^{t_0t_0}$ of the intermediate outputs of $s(1, I, k) \in \mathfrak{L}_I$ is contemporaneous, contributing their effects to the production of $s(1, J, k) \in \mathfrak{L}_J$ concurrently, and the rest will dynamically influence $s(1, J, k)$'s production in the next time period. Thus in time t_1, $s(1, J, k)$ uses not only part of the intermediate outputs produced by $s(1, I, k)$ in time t_1, but also those produced in the previous time period due to the dynamic effect. Finally, we should note that the dynamic effect can be either physically observable (e.g., inventory) or only conceptual (e.g., improvement in human resources) in nature, so the shaded triangles in the figures only symbolize the effect.

3.3 Efficiency measurement

We introduce the mathematical formulations of the proposed network-DEA model and efficiency measures in this section. Following the formulation of LP (3.1) shown earlier, we limit our discussion to the input-oriented measure only, and the technology is assumed to exhibit constant returns-to-scale (CRS). Output-oriented measures can be developed and implemented analogously. Our model describes the situation where each DMU consists of two SDMUs and the first SDMU provides its intermediate outputs to the other SDMU. More specifically, the model depicts a two-SDMU production network, in which the production of the second SDMU is affected by the dynamic effect. The DEA-efficiencies of SDMUs are derived and interpreted as in LP (3.1), and the results are subsequently used to compute our new efficiency measure. We use the new measure to evaluate DMUs and their SDMUs according to their ability to use minimal inputs to produce a given level of outputs in the dynamic production network.

3.3.1 DEA efficiencies: SDMUs

Consider a set of homogeneous DMUs operating over time periods T. Each DMU has two tiers of SDMUs I, J , and each DMU has one SDMU within each tier. Referring to Figure 3.3 (a), we can see that $s(1, I, k) = \mathcal{L}_I^k$ and $s(1, J, k) = \mathcal{L}_J^k$. Using the notations defined earlier, we can identify the following properties:

$$
\begin{aligned}
&n(\mathcal{L}_I) = n(\mathcal{L}_J) = k, n(\mathcal{L}_I^k) = n(\mathcal{L}_J^k) = 1 \\
&n(\mathcal{S}^k) = n(\mathcal{L}_I^k \bigcup \mathcal{L}_J^k) = n(\mathcal{L}_I^k) + n(\mathcal{L}_J^k) = 2, \mathcal{A}^{k_1} = \mathcal{A}^{k_2} \text{ for all } k, k_1, k_2 \in \mathbf{K}.
\end{aligned}
$$

Measuring SDMU's DEA-efficiency is straightforward. Each SDMU is benchmarked with other SDMUs in the same tier set operating in the same time period. Formally, the efficiency of SDMUs can be measured by invoking LP (3.1):

Efficiency of $s(1, I, 0)$ in time t_0:

$$
(\tilde{\vartheta}_{I_1 0}^{t_0}, \tilde{\lambda}_0, \tilde{s}_{P_I I_1 0}^{t_0 -}, \tilde{s}_{Q I_1 0}^{t_0 +}) = f_{CCR}\left((x_{I_1 0}^{t_0}, y_{I_1 0}^{t_0}) \middle| (x_{I_1 k}^{t_0}, y_{I_1 k}^{t_0}) \;\forall k \in \mathbf{K} \right) \tag{3.4}
$$

Efficiency of $s(1, I, 0)$ in time t_1:

$$
(\tilde{\vartheta}_{I_1 0}^{t_1}, \tilde{\lambda}_0, \tilde{s}_{P_I I_1 0}^{t_1 -}, \tilde{s}_{Q I_1 0}^{t_1 +}) = f_{CCR}\left((x_{I_1 0}^{t_1}, y_{I_1 0}^{t_1}) \middle| (x_{I_1 k}^{t_1}, y_{I_1 k}^{t_1}) \;\forall k \in \mathbf{K} \right) \tag{3.5}
$$

Efficiency of $s(1, J, 0)$ in time t_0:

$$
(\tilde{\vartheta}_{J_1 0}^{t_0}, \tilde{\lambda}_0, \tilde{s}_{P_J J_1 0}^{t_0 -}, \tilde{s}_{Q J_1 0}^{t_0 -}, \tilde{s}_{U J_1 0}^{t_0 +}) = f_{CCR}\left((\mathbf{x}_{J_1 0}^{t_0}, z_{J_1 0}^{t_0}) \middle| (\mathbf{x}_{J_1 k}^{t_0}, z_{J_1 k}^{t_0}) \;\forall k \in \mathbf{K} \right), \tag{3.6}
$$
$$
\text{where } \mathbf{x}_{J_1 k}^{t_0} = \left[x_{J_1 k}^{t_0} \; (\alpha_{I_1 J_1 k}^{t_0 t_0} \cdot y_{I_1 J_1 k}^{t_0}) \right]
$$

Efficiency of $s(1, J, 0)$ in time t_1:

$$(\tilde{\vartheta}^{t_1}_{J_10}, \tilde{\lambda}_0, \tilde{s}^{t_1-}_{P_J J_1 0}, \tilde{s}^{t_1-}_{Q J_1 0}, \tilde{s}^{t_1+}_{U J_1 0}) = f_{CCR}\left((\mathbf{x}^{t_1}_{J_1 0}, z^{t_1}_{J_1 0}) \middle| (\mathbf{x}^{t_1}_{J_1 k}, z^{t_1}_{J_1 k}) \ \forall k \in \mathbf{K} \right), \quad (3.7)$$
$$\text{where } \mathbf{x}^{t_1}_{J_1 k} = \left[x^{t_1}_{J_1 k} \ \left(\alpha^{t_1 t_1}_{I_1 J_1 k} \cdot y^{t_1}_{I_1 J_1 k} + \beta^{t_0 t_1} \cdot \alpha^{t_0 t_1}_{I_1 J_1 k} \cdot y^{t_0}_{I_1 J_1 k} \right) \right]$$

where "$\cdot$" in (3.6) and (3.7) denotes the componentwise multiplication of two vectors. Observe that in (3.4) and (3.5) y is the production output, while in (3.6) and (3.7) it is treated as an input. Since t_1 is the final period, it holds that $\alpha^{t_0 t_0}_{I_1 J_1 k} + \alpha^{t_0 t_1}_{I_1 J_1 k} = \alpha^{t_1 t_1}_{I_1 J_1 k} = i_{|Q|}$ where $i_{|Q|}$ is an $|Q|$ vector with all components equal to one. Consequently, model (3.6) and (3.7) will reduce to the conventional DEA model without dynamic effects if $\alpha^{t_0 t_0}_{I_1 J_1 k} = i_{|Q|}$. Before we proceed to introduce the new efficiency measure in the dynamic environment, let us first prove the following theorem, which shows the relationship between DEA-efficiencies of SDMUs and that of their parent DMU.

Theorem 3.3. *In the single-DMU model, if $s(1, I, k)$ and $s(1, J, k)$ are both CCR-efficient in some period, then DMU$_k$ is CCR-efficient in that period.*

Proof. Suppose that DMU$_k$ is not CCR-efficient. Then there must exist some vectors $\tilde{s}^-_{P_I I_1 k}$, $\tilde{s}^-_{P_J J_1 k}$ and $\tilde{s}^+_{U J_1 k}$ and at least one of them is semipositive, such that $(x_{I_1 k} - \tilde{s}^-_{P_I I_1 k}, y_{I_1 J_1 k})$ and $([y_{I_1 J_1 k} \ \ x_{J_1 k} - \tilde{s}^-_{P_J J_1 k}], z_{J_1 k} + \tilde{s}^+_{U J_1 k})$ are both feasible in $s(1, I, k)$'s and $s(1, J, k)$'s respective DEA models LP (3.1). This contradicts the assumption that $s(1, I, k)$ and $s(1, J, k)$ are both CCR-efficient. Thus the result follows. $\square$

It is straightforward to show that Theorem 3.3 can be extended to the multi-SDMU model; i.e, efficiency of all SDMUs implies that of the DMU. Note that the converse of the theorem is not necessarily true. More specifically, the CCR-efficiency of a DMU does not require its SDMU to be simultaneously CCR-efficient, relative to the other SDMUs. To illustrate, consider two DMUs (DMU$_a$ and DMU$_b$) with a simple two-SDMU structure as shown in Figure 3.2. Let $(2, 3, 1, 1)$ and $(1, 1, 1, 1)$ denote (*input of* $s(1, I, \cdot)$, *intermediate output, input* *f* $s(1, J, \cdot)$, *fi a*) of these two DMUs. We can easily see that DMU_b is CCR-efficient but $s(1, I, b)$ is not.

3.3.2 Ψ-efficiencies of SDMUs and DMU

In this section we develop a system of interrelated efficiency indexes that measure the relative efficiency of SDMUs and DMUs. The tier structure of a production network signifies that a network system can be represented as the joint production of multiple tiers. If we continue breaking down the tiers, the same can be applied to describing the relationship between a tier and its SDMUs. We follow this line of thought in developing our efficiency measuring system. Specifically, we start by first estimating the efficiencies of SDMUs, then of tiers, then finally of the entire DMU. In doing so, we can derive the best network performance achievable from a bottom-up fashion; our objective is detect improvement opportunities at each hierarchical level so as to maximize network (overall) performance; our new efficiency indexes also consider the dynamic effect in production.

The developing concept of our approach still adheres to the classical notion of productivity in production economics, namely "*c ı g e ı d ce e ı a e* ." Thus in our two-tier network production model, the minimal input requirements of tiers are computed by applying backward-induction-like techniques different tiers according to the sequence of material flows, at the same time assuming that all SDMU are efficient. The minimal input requirement of a network can be similarly calculated based on that of the tiers in the network.

In view of the dynamic effects existed in the network, we develop new efficiency indexes that consider both the static CCR-efficiency and the dynamic interrelationships among SDMUs. In this chapter we consider the model consisting of two-period, duo-tier with one SDMU in each tier. The input-oriented efficiency indices $\Psi_{J_1 k}$ and $\Psi_{I_1 k}$ are constructed with respect to $s(1, J, k)$ and $s(1, I, k)$, respectively as follows:

$$
\begin{aligned}
\Psi_{J_1 k} &:= \max_{p \in P_J, q \in Q} \left\{ \frac{\sum\limits_{t \in T} x^{*t}_{pJ_1k}}{\sum\limits_{t \in T} x^{t}_{pJ_1k}}, \frac{\sum\limits_{t \in T} y^{*t}_{qI_1J_1k}}{\sum\limits_{t \in T} y^{t}_{qI_1J_1k}} \right\} \\
&= \max_{p \in P_J, q \in Q} \left\{ \frac{\sum\limits_{t \in \{t_0, t_1\}} (\tilde{\vartheta}^t_{J_1k} x^t_{pJ_1k} - \tilde{s}^{t-}_{pJ_1k})}{\sum\limits_{t \in \{t_0, t_1\}} x^t_{pJ_1k}}, \frac{\sum\limits_{t \in \{t_0, t_1\}} (\tilde{\vartheta}^t_{J_1k} y^t_{qI_1J_1k} - \tilde{s}^{t-}_{qJ_1k})}{\sum\limits_{t \in \{t_0, t_1\}} y^t_{qI_1J_1k}} \right\},
\end{aligned}
$$

where x^* and y^* represent the possible minimized input use.

(3.8)

$$
\begin{aligned}
\Psi_{I_1 k} &:= \max_{p \in P_I} \left\{ \frac{\sum\limits_{t \in T} x^{*t}_{pI_1k}}{\sum\limits_{t \in T} x^{t}_{pI_1k}} \right\} \\
&= \max_{p \in P_I} \left\{ \frac{\max\limits_{q \in Q}\{\xi_q\} \cdot (\tilde{\vartheta}^{t_0}_{I_1k} x^{t_0}_{pI_1k} - \tilde{s}^{t_0-}_{pI_1k}) + \tilde{\vartheta}^{t_1}_{J_1k} (\tilde{\vartheta}^{t_1}_{I_1k} x^{t_1}_{pI_1k} - \tilde{s}^{t_1-}_{pI_1k})}{x^{t_0}_{pI_1k} + x^{t_1}_{pI_1k}} \right\} \\
\text{where } \xi_q &= \frac{(\tilde{\vartheta}^{t_0}_{J_1k} \alpha^{t_0t_0}_{qI_1J_1} y^{t_0}_{qI_1J_1} - \tilde{s}^{t_0-}_{qI_1J_1k}) + (\tilde{\vartheta}^{t_1}_{J_1k} \alpha^{t_0t_1}_{qI_1J_1} \beta^{t_0t_1}_q y^{t_0}_{qI_1J_1} - \tilde{s}^{t_1-}_{qI_1J_1k})}{y^{t_0}_{qI_1J_1}} \\
&= \tilde{\vartheta}^{t_0}_{J_1k} \alpha^{t_0t_0}_{qI_1J_1} + \tilde{\vartheta}^{t_1}_{J_1k} (1 - \alpha^{t_0t_0}_{qI_1J_1}) \beta^{t_0t_1}_q - \frac{\tilde{s}^{t_0-}_{qI_1J_1k} + \tilde{s}^{t_1-}_{qI_1J_1k}}{y^{t_0}_{qI_1J_1}},
\end{aligned}
$$

x^* represents the possible minimized input use.

(3.9)

Derivations of (3.8) and (3.9) are recounted as follows. The numerator of (3.8) and (3.9) represents the minimal aggregate input requirement with respect to the aggregate final output in these two periods. The denominators consist of the aggregate inputs used by the SDMU. To compute the numerator of Ψ_{J_1k}, the efficiencies and input slacks of $s(1, J, k)$ in t_0 and t_1 are first derived from (3.6) and (3.7). Ψ_{I_1k} bears a relatively complex structure, because $s(1,I,k)$ is entangled in the dynamic effect that it imposes on $s(1,J,k)$. Note that in both indexes the maximum operator, instead of the minimum, is applied to the ratio. This is because the optimal ratios of reduction of different inputs are not necessarily consistent. For instance, through the backward reduction calculation we may see that, given its aggregate output level, one DMU can reduce its labor input by 10%, while it can only reduce the investment in machinery by 5%. Therefore the maximum operator is taken to ensure that the final output vectors are still producible after implementing this reduction ratio. We now explain this formulation in greater detail.

Similar to the SDMU in $\mathfrak{L}_J$, $s(1,I,k)$ will invoke (3.4) and (3.5) to obtain the required entries of the efficiency index (3.9). Subsequently, we can derive the numerator of (3.9) in two steps corresponding to the production in t_0 and t_1. In t_1, $s(1,I,k)$ first has to reduce its input vector to $\tilde{\vartheta}^{t_1}_{I_1k}x^{t_1}_{I_1k} - \tilde{s}^{t_1-}_{P_II_1k}$ to render itself technically efficient. Secondly, $s(1,I,k)$ has to further reduce its outputs, and thereby its inputs, by a ratio $\tilde{\vartheta}^{t_1}_{J_1k}$ in order to accommodate itself to the input reduction from $s(1,J,k)$ in t_1. So in t_1, $s(1,I,k)$ can reduce its input to $\tilde{\vartheta}^{t_1}_{J_1k}(\tilde{\vartheta}^{t_1}_{I_1k}x^{t_1}_{I_1k} - \tilde{s}^{t_1-}_{P_II_1k})$ and $s(1,J,k)$ can still produce $z^{t_1}_{J_1k}$. Similarly, in t_0, $s(1,I,k)$ can first reduce its input levels to $\tilde{\vartheta}^{t_o}_{I_1k}x^{t_0}_{I_1k} - \tilde{s}^{t_0-}_{P_II_1k}$. In the second step, we need to consider the input reduction from $s(1,J,k)$ in both t_0 and t_1 due to the dynamic effect (see Figure 3.4 for an illustration). This reduction factor, denoted by ξ_q in (3.9), is the ratio of the minimally required level of intermediate outputs to the observed intermediate outputs produced at time period t_0. In particular, the terms within the first pair of parentheses in the numerator of ξ_q correspond to the minimal requirement of intermediate output q for the production of $s(1,J,k)$ in t_0 (results derived from (3.6)); the terms within the second pair of parentheses have a similar meaning except for the term t_1 and the additional decay factor in the formulation (results derived from (3.7)). So (3.9) indicates that the input requirement of $s(1,I,k)$ in t_0 also relates to the performance of $s(1,J,k)$ in both t_0 and t_1 due to the intra-connected network structure and the dynamic effect.

The influence of the performance of $s(1, J, k)$ in t_1 on the index depends on the intensity of dynamic effects that $s(1, I, k)$ contributes to $s(1, J, k)$. This dynamic interrelation will be further discussed in the the next subsection.

We call a SDMU $s(i, I, k)$ input-oriented Ψ-efficient if, and only if $\Psi_{I_ik} = 1$. Based on (3.8) and (3.9), we can observe several properties of these two Ψ-efficiency indexes:

Property 3.4. $\Psi_{J_1k} \in (0, 1]$, and $s(1, J, k)$ is Ψ-efficient

(a) if and only if $s(1, J, k)$ is weakly efficient in both t_0 and t_1, and either $s^{t_0-}_{pJ_1k} = s^{t_1-}_{pJ_1k} = 0$ for at least one $p \in P_J$ or $s^{t_0-}_{qJ_1k} = s^{t_1-}_{qJ_1k} = 0$ for at least one $q \in Q$.
(b) if $s(1, J, k)$ is CCR-efficient in both t_0 and t_1.

Proof. From LP (3.1) we know $x^{t_*}_{pJ_1k} \geq \tilde{\vartheta}^{t_*}_{J_1k} x^{t_*}_{pJ_1k} - \tilde{s}^{t_*-}_{pJ_1k}$, and $y^{t_*}_{qJ_1k} \geq \tilde{\vartheta}^{t_*}_{J_1k} y^{t_*}_{qJ_1k} - \tilde{s}^{t_*-}_{qJ_1k}$ for $* = 1, 2$ and all $p \in P_J$, $q \in Q$. Hence $\Psi_{J_1k} \in (0, 1]$ because input vectors are semipositive (see also Theorem 3.3 in Cooper et al (2006)). Given $\Psi_{J_1k} = 1$, there must exist at least one $p \in P_J$ (or one $q \in Q$), such that equalities hold in the above two inequalities. Thus $\tilde{\vartheta}^{t_0}_{J_1k} = \tilde{\vartheta}^{t_1}_{J_1k} = 1$, and either $\tilde{s}^{t_0-}_{pJ_1} = \tilde{s}^{t_1-}_{pJ_1} = 0$ for some $p \in P_J$ or $\tilde{s}^{t_0-}_{qJ_1} = \tilde{s}^{t_1-}_{qJ_1} = 0$ for some $q \in Q$. Then the sufficiency of (a) is proved. The necessity of (a) can be shown by simple algebraic substitutions. The proof of (b) follows immediately from (a). □

Property 3.5. $\Psi_{I_1k} \in (0, 1]$, and $s(1, I, k)$ is Ψ-efficient

(a) if and only if the following three conditions are all met: (1) $s(1, I, k)$ and $s(1, J, k)$ are weakly efficient in both t_0 and t_1, (2) $s^{t_0-}_{pI_1k} = s^{t_1-}_{pI_1k} = 0$ for at least one $p \in P_I$, and (3) $s^{t_0-}_{qI_1J_1k} = s^{t_1-}_{qI_1J_1k} = 0$, and either $\beta^{t_0t_1}_q = 1$ or $\alpha^{t_0t_0}_{qI_1J_1k} = 1$ for some $q \in Q$.
(b) if $s(1, I, k)$ and $s(1, J, k)$ are CCR-efficient in both t_0 and t_1 and either $\beta^{t_0t_1}_q = 1$ or $\alpha^{t_0t_0}_{qI_1J_1k} = 1$ for some $q \in Q$.

Proof. Similar to the proof of Property 3.4. □

We define the Ψ-efficiency of a DMU as in Definition 3.6. This definition is also applicable in the general case where multiple SDMUs exist in each tier.

Definition 3.6 ($\varPsi$-efficiencies of DMUs). *DMU_k's input-oriented $\varPsi$-efficiency is defined by*

$$\varPsi_k = \left(\prod_{i \in \mathcal{L}_I^k} \varPsi_{I_i k}\right)^{1/n(\mathcal{L}_I^k)} \left(\prod_{j \in \mathcal{L}_J^k} \varPsi_{J_j k}\right)^{1/n(\mathcal{L}_J^k)}$$

and DMU_k is called input-oriented $\varPsi$-efficient if, and only if $\varPsi_k = 1$.

By Definition 3.6, two properties follow immediately from Property 3.4 and Property 3.5.

Property 3.7. $\varPsi_k \in (0, 1]$ and DMU_k is $\varPsi$-efficient if, and only if $s(1, I, k)$ and $s(1, J, k)$ are both $\varPsi$-efficient.

Property 3.8. If DMU_k is $\varPsi$-efficient, then DMU_k is at least weakly efficient in t_0 and t_1.

Figure 3.5 illustrates the hierarchical structure of $\varPsi$-efficiencies developed in this chapter. The figure shows that the efficiency indexes are constructed and calculated in a bottom-up fashion—we compute the efficiency of SDMUs first (CCR and $\varPsi$), which are the elements used to build up the efficiency index at the tier and network level. So naturally the scores at one level can be linked to that at the neighboring levels, as Figure 3.5 shows. Yet the $\varPsi$-efficiencies for SDMUs are computed based on the input requirement corresponding to the total production of the network; thus the index at the lowest level is linked to its contribution to the network production. This points to the heart of our hierarchical system of efficiency indexes: we tap into the processes inside the network to discover more improvement opportunities for the network—nevertheless the index scores for units at lower levels are determined by the units' relative performance contribution to the network, relative to other homogeneous SDMUs. We next summarize the relationships between $\varPsi$-efficiencies and CCR-efficiencies of SDMUs and DMUs.

Network-level measure	Ψ_k	
tier-level measure	$\left(\prod_{i\in\mathcal{L}_I^k}\Psi_{I_ik}\right)^{1/n(\mathcal{L}_I^k)}$	$\left(\prod_{j\in\mathcal{L}_J^k}\Psi_{I_jk}\right)^{1/n(\mathcal{L}_J^k)}$
SDMU-level measure	$\Psi_{I_1k},\Psi_{I_2k},\ldots,\Psi_{I_ik}$	$\Psi_{J_1k},\Psi_{J_2k},\ldots,\Psi_{J_jk}$

Fig. 3.5. Hierarchical structure of Ψ-efficiencies

3.3.3 Discussions on $\boldsymbol{\Psi}$-efficiencies

The first remark is that the Ψ-efficiency of $s(1,I,k)$ depends not only on its own performance, but also on the performance of $s(1,J,k)$ to an extent moderated by the dynamic parameters. We can also see that $s(1,I,k)$ and $s(1,J,k)$ will become independent of each other in production, if there does not exist any connection between these two tiers. In this case, the former intermediate output changes into the final output, and $s(1,I,k)$ is no longer associated with $s(1,J,k)$ in terms of the DMU's final outputs. Therefore its Ψ-efficiency can be measured in a way similar to (3.8).

Property 3.4 indicates that CCR-efficiency is a sufficient condition for $s(1,J,k)$ to be Ψ-efficient, while weakly efficiency is not. Property 3.4 and Property 3.5 together imply that by Definition 3.6 there need not be any Ψ-efficient DMU at all, either because of the internal inefficiency or the production externality due to the dynamic effect. However, the possible non-existence of efficient DMUs can be considered a relative merit of our approach, as compared to the conventional DEA, because the network-DEA model is more sensitive in detecting inefficiencies. If we assume that either intermediate outputs are of equivalent effect in t_1 as in t_0 (i.e., $\beta_q^{t_0t_1}=1$, no decay effect), or they are contemporaneous (i.e., $\alpha_{qI_1J_1}^{t_0t_0}=1$, so the decay factor becomes irrelevant), Property 3.5 is actually quite similar to Property 3.4, except for those conditions related to the efficiencies of $s(1,J,k)$. However, Property 3.5 does not hold when $\beta^{t_0t_1}$ and $\alpha_{I_1J_1k}^{t_0t_0}$ are strictly less than one. In fact, $s(1, I, k)$ is then Ψ-inefficient by default in this two-period model. This is because the utility of a proportion of the intermediate outputs will inevitably be nullified by the decay factor. Definition 3.6 specifies the Ψ-efficiency of a DMU as the product of two geometrical means, which individually can be interpreted as the average Ψ-efficiency of a tier in the DMU. In other words, a DMU's Ψ-efficiencies depend on the Ψ-efficiencies of its tiers, which will further rely on the performance of those SDMUs within the corresponding tier. Property 3.7 shows that a DMU is Ψ-efficient if and only if all SDMUs within the DMU are also Ψ-efficient. Therefore, under some appropriate assumptions on the parameters of dynamic effects, SDMU's CCR-efficiencies can imply DMU's Ψ-efficiencies, which also suggests that the DMU is weakly efficient in both periods (Property 3.8).

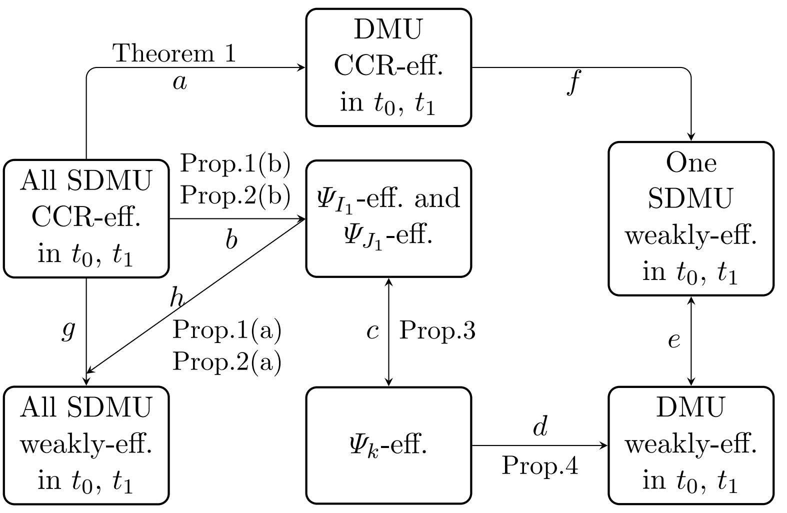


Fig. 3.6. Relationships among Ψ-efficiencies and DEA-efficiencies

Figure 3.6 schematically summarizes the relationships between the Ψ-efficiency and the DEA-efficiency of different production units. This figure readily conveys a new perspective on the connections between static and dynamic efficiencies, and it also provides a road map for decision-makers to reexamine and improve their performance. Links in the figure (i.e., a, b, c and d) are substantiated by the corresponding Theorem or Property annotated beside the link. Link f and g come directly from the definition via e. Link h is affirmed by the above discussion, from which we know that Ψ-efficiencies of SDMUs imply their own weakly efficiencies. Yang et al (2000) proved that a DMU is CCR-efficient if and only if all SDMUs in the DMU are also CCR-efficient. This finding is not entirely compatible to our model (cf. link a in Figure 3.6) due to the discrepant internal structures: in our terminology, the production network in Yang et al. can be described as a single-SDMU, multi-tier production network, in which no linkage exists between tiers. Link e was proved in Castelli et al (2004).

The theorem and properties shown in this chapter are developed for the two-tier, single-SDMU network. We expect the result will also hold for networks with more tiers and SDMUs; however this should be verified in future research.

3.4 Returns-to-scale of production networks

Returns-to-scale (RTS) have been another important aspect of production, in addition to technical efficiency. One interesting question here is how exploring the internal structure of a network can help improve its scale performance. In this section we will look into the relationship between the returns-to-scale properties of the network and those of its sub-processes, and provide a preliminary answer to this question.

Before investigating the RTS properties, let us first check whether introducing network structures will cause problems to the analytical RTS properties of a network (DMU).

We first discuss one invariance property of production networks. Consider now for every DMU_k there are two tiers $\mathcal{L}_I^k$ and $\mathcal{L}_J^k$ inside, and each tier can include single or multiple SDMUs. We use the backward-induction technique introduced in the previous section to calculate the Ψ-efficiency index. Then, if $\mathcal{L}_J^k$ needs to reduce the aggregate use of intermediate outputs produced by $\mathfrak{L}_I^k$ by, say, 20 %, will the subsequent input reduction of $\mathfrak{L}_I^k$ vary if output reductions are not allocated evenly to each SDMU in $\mathfrak{L}_I^k$? One can also relate this situation to the scenario where the demand for a certain product is declining in the market but its impact to different suppliers is asymmetrical. This is an important issue, because otherwise the RTS property of a DMU will lose tractability in the network environment. Define the degree of RTS as the ratio between the proportional increase in inputs and the corresponding proportional increase in outputs. Then the *back-attributively invariant property* means that, if the SDMUs that are being back-attributed have the same degree of RTS[1], the total amount of input saved in this tier is invariant even under different back-attribution schemes, provided that the mix of aggregate intermediate outputs of the downstream tier remains constant after reductions. Specifically, for some $\theta \in (0, 1]$, the constant-mix condition between two tiers can be mathematically represented as:

$$\sum_{i \in \mathfrak{L}_I^k} \sum_{j \in \mathfrak{L}_J^k} \tilde{y}_{qI_iJ_jk} = \theta \sum_{i \in \mathfrak{L}_I^k} \sum_{j \in \mathfrak{L}_J^k} y_{qI_iJ_jk} \quad \forall q \in Q \tag{3.10}$$

where $\tilde{y}_{qI_iJ_jk}$ denotes the reduced level of intermediate output q corresponding to the aggregate input reduction of $\mathfrak{L}_J^k$. So the mix among different intermediate outputs is maintained after reduction. Additionally, denoting the degree of RTS of $s(i, I, k)$ by ζ_{I_i}, the same degree of RTS assumption is equivalent to the following condition:

$$\zeta_{I_i} = \zeta_I \text{ for all } i \in \mathfrak{L}_I^k. \tag{3.11}$$

The above statements can be formally summarized in the following proposition.

[1] This is not to be confused with the CRS assumption in the conventional DEA model, as the latter is a special case of the former.

Proposition 3.9. *Suppose $\mathcal{L}_I^k$ precedes $\mathcal{L}_J^k$ in terms of flows, then the total amount of inputs reduced in $\mathcal{L}_I^k$ by performing backward-induction is back-attributively invariant if and only if all SDMUs in $\mathcal{L}_I^k$ have the same degree of RTS, provided that the intermediate output mix remains constant.*

Proof. See Appendix A. □

As opposed to the assumption of the same degree of RTS in Proposition 3.9, if the technology of $\mathcal{L}_I^k$ exhibits variable degrees of RTS (i.e., for different $i \in I$, $s(i, I, k)$ can produce at different degrees of RTS), then the RTS property will become untraceable, since now different allocation schemes can result in different total input reductions of the precedent tier. Moreover, output reductions itself can lead to changes in RTS of $\mathcal{L}_I^k$. Thus in this chapter we assume constant RTS (CRS) in our efficiency evaluation; in future research, we should relax the assumption to develop more general framework of evaluating dynamic efficiency under "variable" and "variable degrees" of returns-to-scale.

Following Proposition 3.9, two corollaries can be derived (cf. Färe et al (1996), p. 163).

Corollary 3.10. *If $\mathcal{L}_I^k$ and $\mathcal{L}_J^k$ exhibit CRS, then DMU_k also exhibits CRS.*

Corollary 3.11. *Suppose DMU_k is Ψ_k-efficient and denote ζ_k as the degree of RTS of DMU_k, ζ_I as that of $s(i, I, k) \forall i$, ζ_J as that of $s(j, J, k) \forall j$. Then $\zeta_k = \zeta_I \zeta_J$.*

Corollary 1 suggests that the DMU can achieve CRS if all of its constituent SDMUs also operate on CRS. However the reverse is not necessarily true, since one tier with increasing RTS and the other with decreasing RTS can also result in CRS at the DMU level. Färe et al (1996) proved the sufficient condition for a network consisting of a series of technologies to exhibit CRS. Corollary 1 is in line with their finding. However the production network in their study corresponds to a multi-tier version of the single-SDMU model without dynamic effects, which is different from our model. Corollary 2 reveals the causal relationship of the RTS properties between a DMU and its SDMUs. Thus decision-makers have to seek the balance between two tiers to optimize the scale performance. For example, a DMU can increase the overall scale of the tier exhibiting increasing RTS, and diminish the overall scale of the tier exhibiting decreasing RTS. Additionally, the DMU must simultaneously maintain the efficiencies of all its SDMUs and promote a well-connected coordination between two tiers (i.e., incorporating the influence of dynamic effects into decision-makings). Consequently, we can also consider increasing or decreasing the number of SDMUs that possess a specific RTS, so as to improve scale performance and balance supply and demand between tiers (e.g., downsize, merge, enlarge or acquire new SDMUs).

3.5 Numerical example

The proposed efficiency measure is applied to a numerical example consisting of six DMUs and two observation periods t_0 and t_1 (see Figure 3.3(a) and Table 3.2). Following the notation defined earlier, we now have $s(1, I, k)$ and $s(1, J, k)$ for $k = 1$ to 6, and $T = \{t_0, t_1\}$. The control factor $\beta_q^{t_0 t_1}$ is assumed to be unity. $\alpha_{qI_1J_1k}^{t_0 t_0}$ is designated to be 0.7 for all k. The data and the efficiency scores are tabulated in Tables 3.2 and 3.3. It can be seen that no SDMU in $\mathcal{L}_I$ is Ψ-efficient, whereas one SDMU in tier $\mathcal{L}_J$ is Ψ-efficient. Moreover, the mean Ψ-efficiency score of the SDMUs in $\mathcal{L}_I$ ($\approx$0.72) is lower than that of $\mathcal{L}_J$ ($\approx$0.81). This result indicates $\mathcal{L}_J$ outperforms $\mathcal{L}_I$ as a whole. Specifically, only $s(1, J, 3)$ is Ψ-efficient because it is CCR-efficient in t_0 and t_1 (Column 4 and 5 of Table 3.3). This result is clear from Property 3.4 and Property 3.5. Unlike in DEA models, none of the six DMUs achieves Ψ-efficiency (Column 3 of Table 3.3), because they did not use minimal inputs vector x_{I_1} and x_{J_1} to produce the given level of final outputs.

Insights and directions for improvements can be discovered by decomposing the DMU's Ψ-efficiency score into SDMU's Ψ-efficiencies (see the first three columns of Table 3.3). For example, for DMU_1, its inefficiency over these two periods, compared to other DMUs, can be attributed to 27% of (relative) inefficiency in tier 2 and 31% in tier 1, as compared to other SDMUs. This feature can be contrasted with the DEA scores reported in the table: the DEA score score tends to underestimate the inefficiency, because traditional DEA models ignore the dynamic effect and only look at the system's aggregate inputs and outputs; moreover, traditional models are unable to reveal the inefficiency composition among tiers. The feature of efficiency decomposition is a clear advantage over the ordinary DEA analysis, which comparatively reveals deficient information for improving the internal production processes.

Table 3.2. A numerical example and the efficiency

	$I_1(t_0)$		$J_1(t_0)$			$I_1(t_1)$		$J_1(t_1)$		
	input	output	input	int.†	output	input	output	input	int.†	output
DMU_1	87	87	164	60.9	178	82	93	195	119.1	184
DMU_2	79	98	195	60.8	184	94	75	165	104.4	147
DMU_3	95	77	213	53.9	293	75	96	215	119.1	232
DMU_4	75	79	193	55.3	156	97	96	192	119.7	180
DMU_5	92	82	155	57.4	192	70	72	161	96.6	192
DMU_6	78	76	279	53.2	216	98	77	292	99.8	237

† Effective intermediate outputs to $s(1, J, k)$.

Table 3.3. Efficiency measuring results

	Ψ_{I_1}	Ψ_{J_1}	Ψ_k	$\vartheta_k^{t_0\,\dagger}$	$\vartheta_k^{t_1\,\dagger}$
DMU_1	0.69	0.73	0.51	0.63	0.73
DMU_2	0.57	0.62	0.36	0.72	0.51
DMU_3	0.90	1.00	0.90	1.00	1.00
DMU_4	0.63	0.67	0.42	0.64	0.60
DMU_5	0.75	0.84	0.63	0.69	0.89
DMU_6	0.79	0.95	0.75	0.85	0.78

† DMU's efficiency scores given by the CCR DEA model.

3.6 Concluding remarks

In this chapter we develop a new approach to evaluate production networks in a dynamic setting. The approach consists of a system of dynamic efficiency indexes that measure the performance of production units at different levels (e.g., individual sub-processes, tiers, and the network). The feature enables managers to have a system view of the network's performance, and to seek inefficient processes that require improvement actions. The outputs of our approach can add to managerial decision-making, including pinpoint where and how much to improve, determine resource allocation in the network, and set up objective bonus-penalty rules for process owners.

We also show various connections between the new efficiency indexes and the DEA CCR efficiency. In the production network, the RTS properties of DMUs can be characterized by those of its constitutive SDMUs. In all, managers can benefit from our approach to methodically analyzing and seeking for performance improvements in the dynamic production network.

Our model carries several additional implications. This chapter points to an important, yet much-ignored issue in efficiency measuring caused by dynamic effects in a production network. So we should carefully consider dynamic effects when assessing organizational performance, especially for those production units with identifiable internal structures. Similarly, we should also attend to external dynamic effects in production. Therefore the management should pay equivalent attention to the dynamic interactions among DMUs within a larger body of production. Secondly, DMU's efficiencies relate closely to SDMUs' efficiencies, but the former in general do not imply the latter. So exploring the internal structure of a DMU should help detect additional areas for improvement. In practice, however, decision-makers may need to consider the trade-off between the cost of obtaining detailed information about internal activities, and the ensuing economic benefit from additional knowledge of inefficiencies. As for the scale performance in production networks, the finding in this chapter indicates that the returns-to-scale of a production network are determined multiplicatively by those of its sub-processes, which adds to our understanding of RTS of networks regarding the measurement, analysis and improvement of the scale efficiency of a network.

Appendix

Proof (Proof of Proposition 1).

Let $\tilde{\vartheta}_{J_j k}$ be the DEA-efficiency score of $s(j, J, k) \in \mathcal{L}_J^k$. By this score we can identify $s(j, J, k)$'s efficient target, which uses intermediate outputs $\tilde{\vartheta}_{J_j k} y_{qI_iJ_j} - \tilde{s}^-_{qJ_jk} \forall q \in Q$ and input $\tilde{\vartheta}_{J_j k} x_{pJ_j} - \tilde{s}^-_{pJ_jk} \forall p \in P_J$ to produce the given level of final outputs. By the constant-mix assumption (3.10), the following equation holds for the aggregate intermediate output reduction of $\mathcal{L}_J^k$:

$$\sum_{j \in \mathcal{L}_J^k} \left((1 - \tilde{\vartheta}_{J_j k}) \sum_{i \in \mathcal{L}_I^k} y_{qI_iJ_jk} + \tilde{s}^-_{qJ_jk} \right) = \theta \mathbf{Y}_q \; \forall q \in Q$$
$$\text{where } \theta \in (0, 1] \text{ is some constant and } \mathbf{Y}_q = \sum_{i \in \mathcal{L}_I^k} \sum_{j \in \mathcal{L}_J^k} y_{qI_iJ_jk} \tag{3.12}$$

Thus we can omit the subscript q without the risk of confusion. Let $\phi_{I_i} \in [0, 1]$ be the ratio of the total reductions in the intermediate outputs allocated to $s(i, I, k)$, and it thereby has to reduce its outputs by the amount equal to (3.13).

$$\phi_{I_i k} \theta \mathbf{Y}, \text{ where } \sum_{i \in \mathcal{L}_I^k} \phi_{I_i} = 1 \tag{3.13}$$

The reduction in inputs consumed by $s(i, I, k)$ is proportional to its output reductions, because of the assumption that $\mathcal{L}_I^k$ exhibits the same degree of RTS as defined in (3.11). Thus $\zeta_{I_i} = \zeta_I$ holds for all $i \in \mathcal{L}_I^k$. Then the total input reductions can be expressed via:

$$\sum_{i \in \mathcal{L}_I^k} (\zeta_{I_i} \phi_{I_i} \theta \mathbf{Y}) = \zeta_I \theta \mathbf{Y} \sum_{i \in \mathcal{L}_I^k} \phi_{I_i} = \zeta_I \theta \mathbf{Y} \tag{3.14}$$

Equation (3.14) indicates that the total input reduction is invariant with different values of ϕ_{I_i}. This shows the necessity of the condition. To prove the sufficiency, the total reduction in inputs used by $\mathcal{L}_I^k$ can be written as:

$$\sum_{i \in \mathcal{L}_I^k} \zeta_{I_i} \phi_{I_i} \theta \mathbf{Y} = \theta \mathbf{Y} \sum_{i \in \mathcal{L}_I^k} \phi_{I_i} \zeta_{I_i} \tag{3.15}$$

Given that total amount of input saved in $\mathcal{L}_I^k$ is attributively invariant, the summation term on the right side of (3.15) has to be a constant for different $\phi_{I_i} \in [0, 1]$. Thus $\zeta_{I_i} = \zeta_I$ must hold for all $i \in \mathcal{L}_I^k$. This also implies that all $s(i, I, k) \in \mathcal{L}_I^k$ exhibit the same degree of RTS ζ_I in production. $\square$

Part II

Process design approaches in risky and uncertain environments

4

Design warehouse systems under risk: combining DEA and simulation approaches

Decisions in SCM concern setting strategies to improve the future organizational performance, whereas the market nowadays is changing rapidly and full of uncertainty. Therefore it is important to have an effective methodology to model the uncertain future environment. For problems that allow prescription of probability distributions to the source of uncertainty, this chapter develops a novel framework to evaluate the integral performance of production systems. We provide an application of the methodology to evaluating order picking systems with different combinations of storage and order picking policies in a warehouse.

In this chapter, we focus on the application of designing the order picking system in a warehouse. The warehousing literature on order picking mostly considers minimizing either elapsed time or distance as the sole objective, whereas warehouse managers in a supply chain have to look beyond single-dimensional performance and consider trade-offs among different criteria. Thus managers still need a unified and efficient framework to select a portfolio of appropriate order picking policies from a multi-criteria and contextual perspective. Our framework—combining Data Envelopment Analysis, Ranking and Selection, and Multiple Comparisons—provides an efficient methodology to simultaneously analyze several interrelated problems in order picking systems with multiple performance attributes, such as service levels and operational costs. We demonstrate our approach through comprehensive evaluations of order picking policies in three low-level, picker-to-parts rectangular warehouses facing demand variations.

4.1 Introduction

The primary goal of warehouse management is to search for the most efficient way to ensure the functionality of the warehouse in the supply chain, whether the basic distribution operation or other innovative value-adding activities. Driven by the customer's constant demand for faster, better, but cheaper services, the efficiency of warehouse operations becomes crucial in today's competitive market. Order picking—the process of retrieving products from storage in response to a specific customer request—has been considered the most labor-intensive and time-critical process in warehouses (Frazelle, 2002; Tompkins et al, 2003; Ten Hompel and Schmidt, 2007). Order picking processes have a strong impact on the responsiveness of a warehouse; thus ill-managed order picking systems can easily jeopardize warehouse performance and interrupt supply-chain processes. Recent innovations in order picking (e.g., put systems, dynamic storage and picking systems, RFID and voice picking; see De Koster et al, 2007) and challenges (e.g., e-fulfillment) have proved their potency in improving supply-chain performance. Consequently, order picking processes have been viewed as the most important area for performance improvement in warehouse management (Petersen, 2000; De Koster et al, 2007). In practice, policies used to control order picking systems include (*i*) storage policies (*ii*) order batching, and (*iii*) picker routing (De Koster and van der Poort, 1998; De Koster et al, 1999; De Koster et al, 2007). Although many studies have been devoted to each individual area, two major issues are still left unresolved.

First, warehouse managers usually have to premeditate which policy combination to employ, rather than selecting each type of policy in isolation. Decision problems in the realm of warehouse control all bear a strong interrelation (Rouwenhorst et al, 2000)—the usefulness of individual order picking policies depends strongly on the other complimentary policies (De Koster et al, 2007), and collectively these policies link closely to other aspects of warehouse management; for example, warehouse design, and downstream logistic coordination (Gu et al, 2007). Therefore, to pursue optimal performance, managers should integrate these warehousing problems into a single decision problem, and consider possible interactions among all adopted policies. The literature, however, does not clarify the interaction of employing one policy in combination with others. Rouwenhorst et al (2000) and De Koster et al (2007) point out that, most warehousing research focuses on a specific order picking situation or dimension, and few authors address combinations of these decision problems.

The second issue relates to the dimension of the performance metrics used to gauge the performance of order picking systems. The literature on order picking mostly focuses exclusively on a single objective (e.g., total travel distance and total fulfillment time) in specific order picking situations. There are other objectives—utilization of space and labor, costs and service levels—which are also important and should also be subsumed into decision criteria at once (Rouwenhorst et al, 2000; De Koster et al, 2007; Ten Hompel and Schmidt, 2007). Petersen et al (2005) consider both travel distance and total fulfillment time in their simulation study of order picking policies. However, they treat these two objectives separately, and therefore the trade-off between objectives is not considered.

This chapter proposes an innovative framework to overcome the above-mentioned issues. In particular, our framework integrates several approaches. We use Data Envelopment Analysis (DEA) to evaluate the performances of different policy combinations through Monte Carlo simulation—such a procedure of simulation optimization is generally referred to as sample-path optimization (Robinson, 1996). DEA is particularly apt in our case because of its capability to evaluate multi-input, multi-output systems with minimal assumptions on the transformation process. In this study, we will evaluate an order picking system's performance based on three criteria: the time used to complete picking tasks, the number of picked items, and the service level achieved. DEA also has well-explored statistical properties (Simar and Wilson, 2000). Several empirical studies have used DEA to benchmark warehouse operations (Hackman et al, 2001; McGinnis et al, 2005; De Koster and Balk, 2008). DEA has some structural and theoretical similarity with multi-objective optimization (Joro et al, 1998): both approaches regards performance evaluation from a multi-dimensional perspective; yet in the latter approach we need additional preference information to select an efficient solution from the efficient frontier.

Our experimental design is governed by the subset selection algorithm. The algorithm uses the two-stage sampling procedure to identify a subset of superior policy combinations, whose size can be pre-specified by the warehouse manager. This feature is particularly crucial when numerous policy combinations exist at the beginning of the planning process. Selected policy combinations in the subset are then grouped using multiple comparisons according to policy performance. Based on the groups and evaluation results, warehouse managers can select which policy combination to adopt according to their preference or experience with the warehouse environment. By the joint use of these approaches, the framework affords flexibility and efficiency in analyzing systems with multiple performance and policy dimensions. Our framework also opens up a new way to a wide range of operational management problems with similar characteristics.

The remainder of this chapter is organized as follows. In the following section, we briefly review warehousing processes and order picking policies. The methodology of this research is presented in Section 3. In Section 4, we demonstrate the approach through an example of low-level, picker-to-parts order picking systems, which form the majority of order picking systems in practice. Section 5 concludes the findings of this study.

4.2 Backgrounds and preliminaries

In this section, we discuss relevant aspects of warehouse operations and order picking heuristics. We should note that the order picking policies covered in this chapter are not exhaustive, and that other warehousing decisions associated with order picking may relate to different performance indicators; for example, (i) warehouse design and management: warehouse investment costs, warehouse throughput, response time, storage capacity and yard management (Rouwenhorst et al, 2000), (ii) supply-chain coordination: inventory management and (de)centralization of decision making in a supply-chain (Simpson and Erenguc, 2001).

This chapter, however, does not intend to draw a decisive conclusion about the performances of all order picking policies within the widest scope of consideration. Our aim is to provide a general platform to efficiently select an appropriate set of policies based on the specific circumstance and technology encountered. Our methodology can be easily adapted when both additional decision dimensions and performance attributes are concerned. Next we provide an overview of the warehousing processes.

4.2.1 Overview of warehouse operations

In practice, warehouse management can be divided into design and operational phases. Based on the characteristics of the customers' orders and the company's order fulfillment strategy, several strategic decisions are taken in the design phase: these include the design of warehouse size, layout, equipments and workforce planning. Subsequently, operational policies, such as storage and order picking policies, are deployed to deliver customer orders in a timely and cost effective way.

Figure 4.1 illustrates a typical (albeit non-comprehensive) flow of warehouse operations. The warehouse operations are first triggered by the delivery notification from the supplier. Upon arrival, items will be inspected for defects, and then transformed into storage units and putaway in the reserve area in the most economical way (e.g., on pallets in racks). The forward area (e.g, shelf racks) is replenished from the reserve area according to the storage policy adopted. When the customer orders arrive, a picking command will be released to the

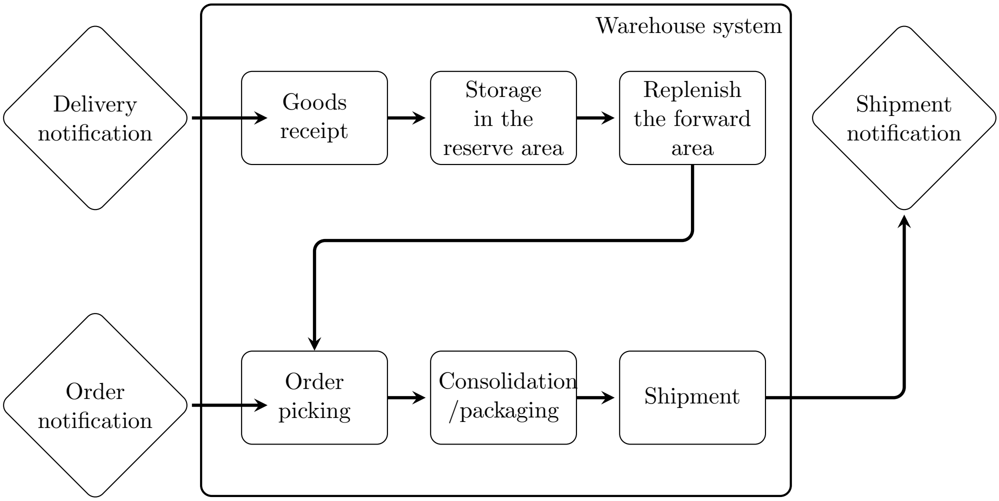


Fig. 4.1. Typical process flows in warehouse operations

shop floor, and correspondingly order pickers will retrieve items from the forward area. Pickers move along the storage aisles with a picking cart and pick orders in accordance with the order picking policies used. The picking cart has space for a certain number of order containers, which allow pickers to separate the picked items by order. In this chapter, we focus on the situation where order-splitting is not allowed and a "sort-while-pick" operation is used. In particular, in the "sort-while-pick" operation, items are sorted right after they are picked. So consolidation is not required after each picking tour; the trade-off is the additional time needed to sort each picked item into different containers on the picking cart. Finally, when the sorted products are packaged, a shipment notification will be issued and orders will be shipped to their destinations.

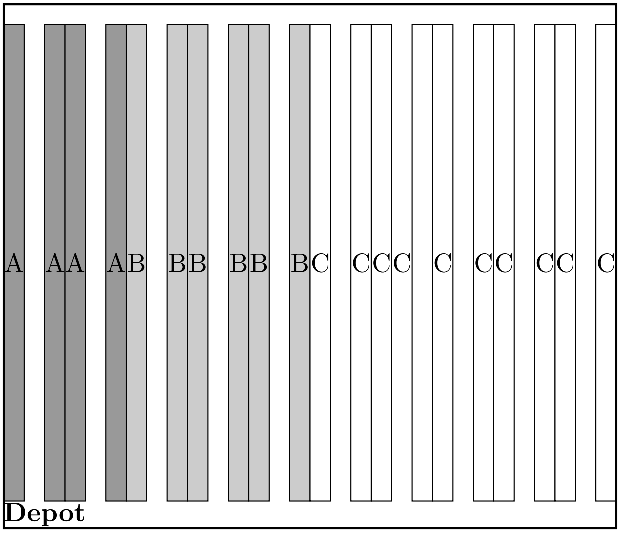
Order picking policies consist of various decisions to efficiently retrieve items in response to customers' demand. Storage policies, however, have been found to interact substantially with the order picking process (e.g., Petersen, 1999, Petersen et al, 2004). Therefore, we include storage policies in the analysis, along with three other dominant decisions in the operational phase (i.e., batch sizing, order sequencing and routing decisions), which form the central part of the research in warehouse operations (Gu et al, 2007).

4.2.2 Storage and order picking policies

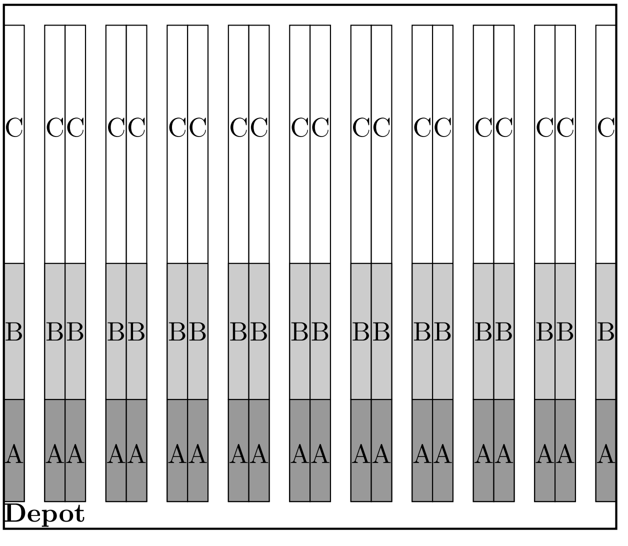
Storage policies are the rules deciding the storage position of incoming items. Several storage assignment methods have been proposed in the literature (see De Koster et al, 2007). In this chapter, we limit our attention to the class-based storage policies. The class-based storage method—arranging storage positions by the demand frequencies—can be seen as a natural reaction to different turn-over rates of products. Le-Duc and De Koster (2005) indicate that class-based methods are widely used in practice because of the ease to maintain and implement. They also show that implementing class-based methods within a proper layout design (e.g., depot and cross aisle positions) can improve the throughput of warehouse operations.

Based on the frequency with which the items are ordered, class-based methods assign items to one of the several predetermined storage classes. Typically, the number of classes is limited to three—"A" represents the class of fastest-moving items, "B" includes the class of second fastest-moving items, and "C" covers the rest. The storage within a dedicated area is randomly assigned. These class areas can be positioned in a warehouse in different ways. We define ABC-1 as the situation where each aisle belongs to only one class, and ABC-2 as the other alternative in which classes are allotted across aisles. Figure 4.2 graphically illustrates these two storage methods. In practice, the choice between ABC-1 and ABC-2 may depend on various factors: the routing policy that pickers use, prevention of congestion, the presence of simultaneous replenishing processes, and many others.

Table 4.1 tabulates the storage settings used in this chapter; so in total we consider five storage policies: *random storage*, *skewed and medium ABC-1* and *skewed and medium ABC-2* (see Table 4.2). Specifically, in skewed ABC, 80% of the most-frequently ordered items occupy 20% of the shelf space, while medium



(a) ABC-1



(b) ABC-2

Fig. 4.2. Top view of the pick area with skewed ABC-1 and ABC-2 storage allocations

Table 4.1. Storage specifications (ordering frequency/storage space(%))

Policy	A-class	B-class	C-class
Skewed	80/20	15/30	5/50
Medium	50/30	30/30	20/40
Random	(1/3)/(1/3)	(1/3)/(1/3)	(1/3)/(1/3)

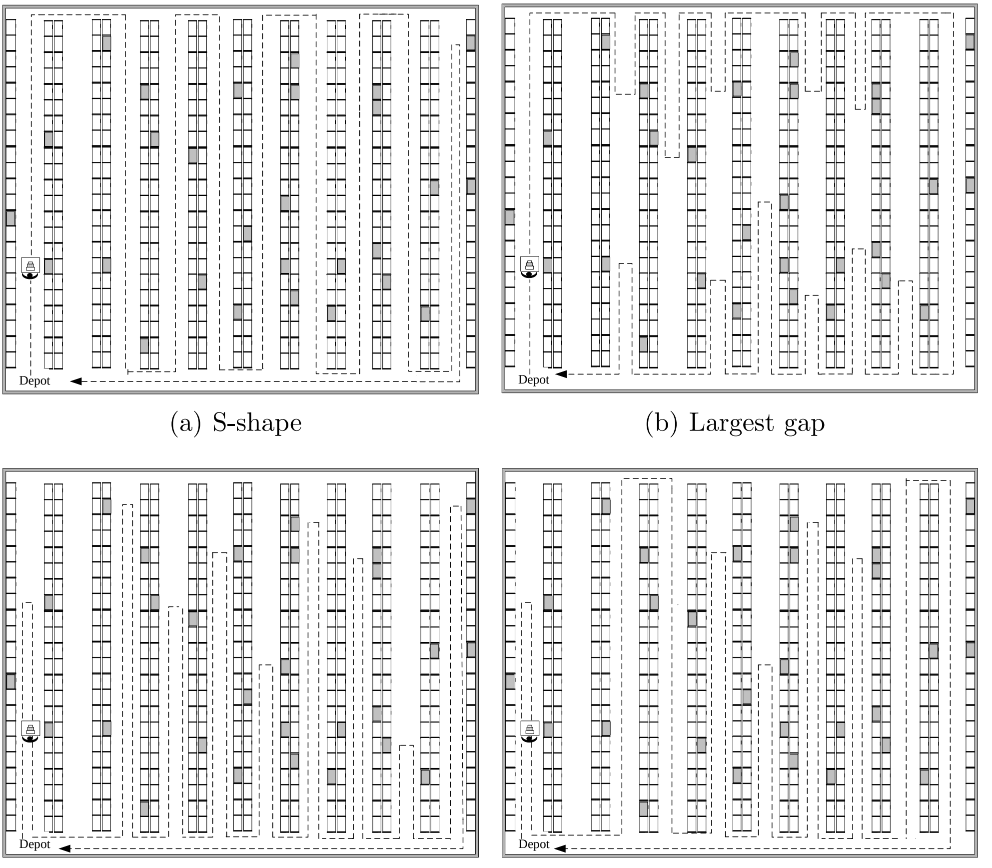
ABC has 50% of the items covering 30% of the shelf space, and so on. Figure 4.2 illustrates the allocation of storage space under ABC-1 and ABC-2 in the skewed case.

Table 4.2. Experimental factors and levels

Factors	Levels	Policies
Picking cart capacity (c)	3	(1) 12
		(2) 24
		(3) 48
Storage policies (s)	5	(1) Random
		(2)(3) ABC-1 (skewed and medium assignment)
		(4)(5) ABC-2 (skewed and medium assignment)
Order sequencing (b)	2	(1) First-Come-First-Served
		(2) Earliest-Due-Time
Routing policy (r)	4	(1) S-shape
		(2) Largest gap
		(3) Return routing
		(4) Combined routing

Order sequencing is the method of partitioning a set of orders into a number of subsets (batches), each of which can then be retrieved by a single picker in a single picking trip. One batch can only contain orders whose total number of items is less than or equal to the picking cart capacity, and orders have to be picked in full. Therefore, the number of orders in one batch is not necessarily identical to that of another; the number depends on the order sizes and the cart capacity. We consider two often-used sequencing policies in this chapter: First-Come-First-Served (FCFS) and Earliest-Due-Time (EDT) policies. FCFS is common in practice because of its simplicity in implementation; see De Koster et al (1999) and De Koster et al (2007). The adoption of EDT comes from its close link to the service level, which is one of the most important performance indicators in warehouse management. For a reference and discussion, see p.486 in De Koster et al (2007), Section 3.2 in Pinedo (2002), and Elsayed and Lee (1996). When orders arrive, the FCFS policy combines orders according to their arrival time until: (i) with the addition of the next order in line, the number of items in the batch will exceed the cart capacity, or (ii) the current order finishes the cart to its capacity. Under this policy, pickers will start picking when either (i) or (ii) occurs. Orders unable to be included in the current batch (e.g., in situation (i)) and orders arriving before pickers return to the depot will be grouped in the next batch according to their arrival time. Slightly differently, the EDT policy groups and releases orders according to the sorted sequence of due time, instead of arrival time considered in FCFS.

Routing policies determine the sequence of items to be picked in a picking trip. The objective is to minimize the order picker's total travel distance. Therefore, when pickers travel at a constant speed and there is no congestion, routing polices can help to minimize the total travel time as well. Routing policies have received considerable attention in the warehousing literature (De Koster et al, 2007; Gu et al, 2007). Four often-used routing policies are considered in this chapter (see Table 4.2). Figure 4.3 illustrates these routing methods in a rectangular warehouse without cross-aisles. When the S-shape policy, also known as traversal routing, is implemented, pickers sequentially enter and travel through the aisles containing at least one item to be picked. In the return routing, pickers enter and exit each aisle on the same side. In the largest gap heuristic, pickers



(a) S-shape (b) Largest gap

(c) Return (d) Combined

Fig. 4.3. Illustration of the routing policies

enter an aisle by return routing until the largest gap is reached, and the remaining items (if any) are picked from the other side of the aisle. The gap is defined by the distance between two adjacent picks, or the first pick to the front aisle, or the last pick to the back aisles. Combined routing involves the traverse patterns of S-shape and return routing: the target aisles can be either traveled through or accessed from one side only; which way to use will depend on the outcome from dynamic programming. For further details on routing policies, readers are referred to Roodbergen and De Koster (2001). Finally, although optimal routing algorithms are available, heuristics mentioned above are more widespread in practice because they are more convenient to implement and understand, require less computational efforts, and are easy to adapt if pickers' starting/ending positions change or the warehouse layout changes. These heuristics are also less prone to omission of picks because they generate more consistent routes (Petersen, 1999). The impact of layout (i.e., size, length/width ratio, depot location and cross-aisles), and storage and routing policies on order picking throughput can be interactively experienced at the Erasmus Logistica website (Oudijk et al, 1999).

To facilitate later discussion, we define policy sets by:

$$\Omega := C \times S \times B \times R = \{(c, s, b, r) | c \in C, s \in S, b \in B, r \in R\}. \tag{4.1}$$

The member of Ω is called a *policy set*; C, S, B and R represent the sets of available policies in their associated dimension, namely picking cart capacity, storage policies, order sequencing policies and routing policy, respectively. Similar to the real-world decision making, each policy set will be treated as an entity for evaluation. Therefore, we consider 3*5*2*4=120 policy sets (c_1 to c_3, s_1 to s_5, b_1 to b_2, r_1 to r_4 ; see Table 4.2), which represent the choice set of warehouse managers.

4.3 The evaluative framework

Our evaluative framework consists of two main phases. In the preparatory phase, warehouse managers need to determine experimental parameters and policy sets to be analyzed in experiments. In the analytic phase, we use simulation procedures to assess the performance of policy sets: we apply a subset selection algorithm embedded within DEA to reduce the problem to a set of superior policies, instead of searching for the best policy set only; policy sets in the selected subset are then classified by multiple comparisons according to the obtained simulation data. This feature offers added flexibility often required in warehouse operations, as external factors may change and some intervening factors may not be easily modeled (e.g., hidden costs like personal training, higher error rates during the adaptation phase of a new policy set, and coordination issues in operation). Moreover, finding the best policy may be time-consuming for large-scale problems. These superior policies may also turn out to have only incremental differences in performance. Therefore, instead of seeking for the "best" design in a static setting, warehouse managers would prefer a larger choice set, and finalize the design parameters according to their professional experience and understanding of the systems. In this section, we first introduce the DEA model and our motivation for using DEA; subsequently we detail the mechanism of the evaluative framework.

4.3.1 Performance evaluation with DEA models

As introduced in preceding chapters, DEA is a useful tool to compare the relative performance of decision alternatives, in which multiple inputs are used to obtain multiple outputs. DEA has the merit that it relies on only few general assumptions on the input-output transformation process (see Simar and Wilson, 2000). In the field of Ranking and Selection (R&S), several approaches capable of handling multiple performance measures also exist; however, these approaches have their own limitations. Butler et al, 2001 propose a two-stage selection procedure that incorporates the multiple attribute utility (MAU) theory. This approach requires an assumption about the functional form of utility functions and elicitation of the preference weights over multiple performance measures, and therefore difficulties can arise in implementation. Kim and Nelson (2007) state that the approach becomes inefficient for 20 or more systems. Evans et al (1991) point out that assessing multi-attribute value functions in multi-criteria optimization can face great difficulty in implementation when the number of criteria increases.

Kleijnen (2008) develops the generalized response surface methodology, which can accommodate multiple responses from a simulation system—analyzers pre-select one response as the objective and the others as constrained variables.

The system is then evaluated through constrained simulation optimization. This methodology, however, still requires setting up an aspiration level for each constrained response beforehand, and the optimization is limited to one selected response. Other similar approaches include, for example, Andradóttir et al (2005) and Batur and Kim (2005); see also Kim and Nelson (2007) for a discussion on the limitations of these methods.

There are also R&S approaches based on multi-objective optimization (see, e.g., Lee et al, 2004b, 2007), but these approaches require some additional assumptions. In Lee et al (2004b) and Lee et al (2007), for example, the probability distributions of objectives are required to be independent from one another, which is rarely true in practice.

Unlike the above approaches, DEA is free from these requirements. For the DEA model, we define the input of a policy set k as the operational costs (x_k) that it takes to fulfill the order picking task, and the output as the number of handled items (z_k) and the corresponding service level (y_k) that the policy set achieves, which is given by the percentage of orders picked before their due times. The specification of the input and output variables accords with the real-life situation in a supply chain: using minimal costs (x_k) to handle more order picking tasks (z_k) while maintaining a high service level (y_k) to their customers. The relative efficiency of policy set k within Ω can be measured by LP (4.2):

$$\min \theta_k \tag{4.2a}$$

$$s.t. \quad \sum_{i=1}^{|\Omega|} \lambda_i x_i \leq \theta_k x_k, \tag{4.2b}$$

$$\sum_{i=1}^{|\Omega|} \lambda_i y_i \geq y_k, \tag{4.2c}$$

$$\sum_{i=1}^{|\Omega|} \lambda_i z_i \geq z_k, \tag{4.2d}$$

$$\lambda_i \geq 0, \ \text{for } i = 1, \ldots, |\Omega|. \tag{4.2e}$$

The model, first introduced in Charnes et al (1978), is called the input-oriented CCR DEA model. The core features of the model are twofold. First we need to define the set of feasible production plans: a production plan is defined as the joint input and output vector (x_k, y_k, z_k); subsequently, the efficiency of a production plan can be measured by its relative distance to the boundary (or frontier) of the feasible set.

The set of feasible production plans is derived as follows. The left-hand-sides of (4.2b)–(4.2d), together with (4.2e), define the boundary set of feasible production plans to be all nonnegative linear combinations of observed production plans (i.e., a polyhedron cone generated by all observed production plans); the inequality signs of (4.2b)–(4.2d) imply that, if (x_k, y_k, z_k) is a feasible production plan, then so is $(x_k + \alpha, y_k - \beta, z_k - \gamma)$, where α, β and γ, are arbitrary positive numbers (i.e., slack variables in LP formulations) such that the input/output variables remain non-negative; that is, if we increase the inputs and/or reduce the outputs of a feasible production plan, the new production plan will still be feasible. So all observed production plans are essentially "enveloped" by the boundary set defined above.

Once the set of feasible production plans is defined, the objective (4.2a) is to minimize the contraction factor θ_k of input x_k, such that $(\theta_k x_k, y_k, z_k)$ is still attainable. Denote the optimal value of the model by θ_k^*. Then $\theta_k^* x_k$ is the minimal costs required to handle z_k items with the service level y_k under current production technology. So θ_k^* provides a direct indication of the *relative efficiency* of policy set k among its peers: θ_k^* less than unity means that policy k overuses costs by a proportion of $1 - \theta_k^*$, given the final service level and the number of handled items. Thus the smaller the value of θ_k^*, the more inefficient k is. On the other hand, if θ_k^* is equal to one, k is relatively efficient because it uses minimum costs to obtain a given output level. For more details and various extensions of DEA models, we refer to Cooper et al (2000).

Algorithm 1 Main steps of the evaluative framework

1: specify: Policy sets to be simulated, Warehouse size and Picker's capabilities, Demand distributions, Subset Selection parameters (P^*, m, δ, n; see Appendix A), the overall significance level α for multiple comparisons.
2: **repeat** steps 3 to 8 for n times.
3: **for** policy set $i = 1, \ldots, |\Omega|$ **do**
4:    generate a fixed number of orders according to Demand distributions.
5:    Invoke policy set i to pick the generated orders.
6:    **return** operation costs (x_i), service level (y_i) and the total number of items (z_i).
7: **end for**
8: compute the DEA model (4.2) to obtain θ_i^* for $i = 1, \ldots, |\Omega|$.
9: **return** the number of additional replications ($N - n$) as required in the Appendix A algorithm; then repeat steps 3 to 8 for ($N - n$) times.
10: use the Appendix A algorithm to obtain a subset consisting of the m most efficient policy sets.
11: construct simultaneous $(1 - \alpha)$ confidence intervals (SCIs) of pairwise differences $(\bar{\theta}_i^* - \bar{\theta}_j^*)$ for the m selected policy sets, where $\bar{\theta}_i^*$ denotes the mean efficiency of policy set i.
12: create disjoint efficiency subsets of these m selected policy sets by identifying groups with non-overlapping SCIs.

4.3.2 Determining policy sets and experimental parameters

Alg. 1 details the stepwise procedures for implementing our framework. The first step is to prescribe all policy sets defined as in Eqn. (4.1)—warehouse managers can determine which policy components to include, either by their professional experiences or expert opinions. This step forms the reservoir of all candidate policies. Additionally, we need to specify parameters for the simulation: (i) warehouse size (i.e., the number of aisles, the aisle length, the storage capacity per aisle, the distance between two aisles), (ii) demand characteristics (i.e., the distribution of order size, arrival pattern, and order due time), (iii) picker's capabilities (i.e., average walk velocity, time required to pick and sort an item), and (iv) parameters related to subset selection procedures (see Appendix A for details). Subset selection methods will next be introduced.

4.3.3 Analytic procedures

Subset selection procedures

We use Koenig and Law's method to efficiently sort out the group of superior policy sets. This method also gives the minimal number of replications required to select the subset, while satisfying the user-defined probabilistic criterion. Recent advances in the R&S field provide more sophisticated models for specific issues, such as non-normality and dependence of simulation output data, and using Common Random Numbers to increase experimental efficiency (Chick and Inoue, 2001a; Kim and Nelson, 2007; Tsai et al, 2008). Sullivan and Wilson (1989) develop a similar approach, in which they use a more involved computational procedure to select subsets with a bounded random size; other approaches include simulation budget allocation (Chen et al, 2000) and the Bayesian approach (Chick and Inoue, 2001b). We refer to Kim and Nelson (2006) and Swisher et al (2003) for a good introduction and overview of the recent development of R&S and its relation to other approaches. These new approaches can be incorporated into our framework to replace the subset selection method used in Algorithm 1. These cited methods, however, mostly aim at identifying the best policy only. We adopt Koenig and Law's method in our framework to obtain multiple superior policy sets leading to greater flexibility in choice for managers.

In step 1, the algorithm requires input parameters for Koenig and Law's method; see Appendix A. The parameter P^* is the probability of correctly selecting a subset containing the best m policy sets. In the method, we first implement n pilot runs; the number of additional replications will depend on the results of the first-stage sampling. If the difference between the mean efficiencies of two policy sets is less than δ^*, then these two sets are considered equal in performance.

An elaboration of the subset selection procedure can be found in Koenig and Law (1985).

Steps 3–8 in Algorithm 1 constitute the main body of our simulation procedures. Following real warehouse operations, we first generate a fixed number of orders according to the predetermined distributions of order arrival rates, due times and sizes; a new set of orders will be *independently* simulated for each policy set. The number of orders is fixed to resemble the cyclic operation intervals of a warehouse (e.g., daily, weekly operations); therefore warm-up periods are not considered in the simulation. Policy sets are then invoked to pick and sort the generated orders. The intermediate outputs from the simulation are two performance measures: operational costs x_k and service level y_k with respect to policy set k. Operational costs are defined to be equivalent to labor costs, which are the product of the total makespan and the unit cost. Service level is measured by the percentage of orders picked before their due time. In step 8 we apply DEA to these two measures and the number of picked and sorted items z_k as described earlier. After each replication, we obtain a random sample from the efficiency distribution of a policy set.

Methods of multiple comparisons

In this chapter, Tukey's method (for unequal sample sizes also called Tukey-Kramer method) is used to compare pairwise differences in efficiencies. Tukey's method can construct simultaneous confidence intervals (SCIs) of all pairwise differences with the overall significance level exactly at α; see Benjamini and Braun (2002) for a thorough review on the method; readers are also directed to Appendix B for a short introduction to Tukey's method.

Having the SCIs, we can create partitions of the selected subset by identifying groups of policy sets with non-overlapping SCIs of efficiencies. In particular, we define the efficient subset as the collection of the policy sets having equally highest mean efficiency scores in the statistical sense; so policy sets in the efficient subset have higher mean efficiencies than all other policy sets not in the subset. Therefore, there might be more than one policy set in the resultant efficient subset. Note that the notion of "efficient subset" is relative: policy sets in the efficient subset are not necessarily efficient in each simulation run (i.e., estimated mean efficiency score=1). Analogously, we can repeat this procedure to construct a secondly efficient subset for the policy sets not in the efficient subset. In Figure 4.4, for example, consider the SCIs constructed by Tukey's method between four policy sets (A to D). From the figure we can see that the efficient subset includes policies A, B and C (because A is not significantly more efficient than B, and neither is B to C), while D is the only member of the secondly efficient subset.

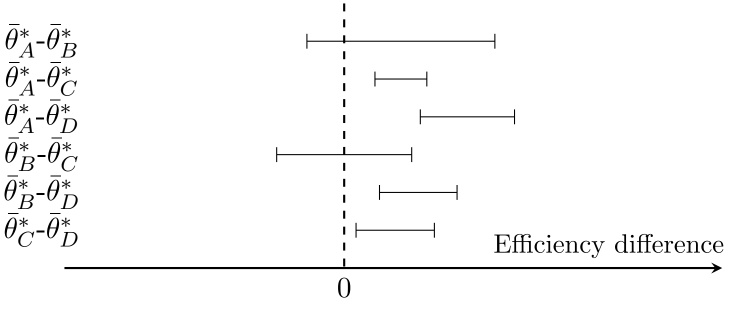


Fig. 4.4. Identifying efficient subsets

Applying subset selection also contributes to the power of Tukey's method, because performing comparisons over the subset m, instead of the entire Ω, could in general result in smaller SCIs. For different interests and purposes, other methods for multiple comparisons can also be applied to our framework: for example, Hsu's MCB test (Multiple Comparisons with the Best), and Dunnett's MCC test (Multiple Comparisons with a Control); see Hsu (1996) for detailed discussions on these multiple comparisons methods; Matejcik and Nelson (1995) show the equivalence of indifference zone rankings and MCB procedures, so both can be obtained simultaneously from the same experiment.

Finally, the statistical validity of using these two approaches together can be maintained at a sufficient level. In particular, the probability of making a correct subset selection and multiple comparisons is at least $P^* \cdot (1-\alpha)$. For example, if by convention we set the probability criterion P^* in subset selection to be 0.95 and $\alpha = 5\%$ in the Tukey's test, then we can still have a fair level of confidence (90.25%) about the analysis results.

4.4 Illustrative examples

A company wants to respond to foreseeable changes in the demands by adjusting the order picking operation of its three warehouses. Three possible demand scenarios are created in contrast to the base scenario: (i) increased arrival rate and large order size, (ii) increased arrival rate with base order size, (iii) base arrival rate with increased order size. Warehouse-1 in question has 10 parallel aisles with a length of 20 m and the center distance between two aisles equal to 2.2 m. The number of item locations per aisle is 20*2. Additionally, the company has two other warehouses in this district facing the same market situations. With also 2.2 m identical center distance between two aisles, warehouse-2 has 5 parallel aisles with a length of 40 m, while warehouse-3 has 20 parallel aisles with a length of 10 m. Apparently, these three warehouses have the same size but different shapes (i.e, different ratios between the length and the width of the warehouse).

Applicable storage and order picking policies/technologies (a total of 120 policy sets) are shown in Table 4.2; the parameters for three scenarios and warehouse dimensions are listed in Table 4.3 and Table 4.4. In all three warehouses, the picker travels with an average speed 0.7 m/sec when the picking cart with a capacity of 12 items is used. The picking and sorting time for one item follows a normal distribution with mean and variance specified in Table 4.4. We also assume that the picker's average travel speed decreases when the cart capacity increases, whereas the setup time for one picking trip and the average sorting time grows with the cart capacity (see Table 4.4). These assumptions reflect the fact that the larger

Table 4.3. Experimental settings

Parameters	Base scenario	Scenario-1	Scenario-2	Scenario-3
Order arrival rate	0.2	1	1	0.2
Order size[1]	4	8	4	8
Due time[2]	|N(60,100)|	|N(60,100)|	|N(60,100)|	|N(60,100)|
	Number of aisles	Length	Distance[3]	Positions/aisle
Warehouse-1	10	20 m	2.2 m	40
Warehouse-2	5	40 m	2.2 m	80
Warehouse-3	20	10 m	2.2 m	20

[1] Approximated means of the censored Poisson distribution.
[2] Normal distribution N(mean, variance) in minutes; $|\cdot|$ represents the absolute value.
[3] The distance between the center of two neighboring aisles.

Table 4.4. Picker-related parameters

Picking cart capacity	$c = 12$	$c = 24$	$c = 48$
Setup time (sec)	60	85	100
Travel speed (m/sec)	0.7	0.5	0.35
Picking time (sec/item)	$\mid N(10,1) \mid$	$\mid N(10,1) \mid$	$\mid N(10,1) \mid$
Sorting time (sec/item)	$\mid N(3,0.5) \mid$	$\mid N(5,0.8) \mid$	$\mid N(8,0.1) \mid$

the capacity is, the more probable more orders will be contained in one batch; thus order pickers need additional sorting time to ensure the picked items are correctly grouped. The total elapsed time for one picking trip is the sum of setup time, travel time, picking time and sorting time during a trip. Given a fixed labor cost rate (per man-hour), cost minimization is equivalent to minimizing the total elapsed time of all orders.

Following Algorithm 1, we choose 120 policy sets, and specify the parameters for subset selection to be $n = 10$, $m = 10$, $\delta^* = 0.03$ and $P^* = 0.95$ (see Appendix A for notations); the overall significance level α in Tukey's method is 5%. Subsequently, in each replication we generate the order size, arrival time and due time of 1000 incoming orders according to the parameters in Table 4.3. Order sizes are generated by a Poisson random number plus 1 to avoid an order size of zero; order sizes larger than 12 (the lowest capacity of picking carts) are censored, because order-splitting is not allowed. The order arrival follows a Poisson process, and the order due time is generated based on half-normal distributions. For each policy set, we independently generate a new set of orders and then repeat the procedure, since independence among systems is required in our subset selection process (see Appendix A). After all policy sets complete their 1000 orders, their efficiency will be evaluated by the DEA model; then the replication ends.

Subsequently, we use the Appendix A algorithm to pre-screen 120 policy sets to the best 10. Tukey's method is then applied to the selected subset, and the first and the second efficient subsets are derived as described in Section 3.3. We implemented the simulation experiments by running Matlab R2007b on a laptop computer with Intel Pentium4-M 1.73 GHz CPU and 512 MB RAM. The average elapsed time of one replication for all policy sets in the base scenario is 178.8 seconds; so on average it takes around 1.5 sec to complete the order picking for one policy set.

Tables 4.5 and 4.6 summarize the result of our simulation experiments. In the table we show the efficient subsets, their within-group mean efficiencies in different scenarios and warehouses, and the number of replications used (N) in the experiments. The end results for the recommended policy sets can be viewed from four different perspectives. Specifically, the company can examine the results from the global perspective, the perspective of partially-fixed policy sets and the dimension-wise perspective; the company can also compare the performances of policy sets operating in different warehousing environments.

4.4.1 Global comparisons

Table 4.5 shows the global ranking of the analysis up to the secondly efficient subset. By global comparisons, the managers can have a broad overview of the performance of all available policy sets, and select the preferable policy set from

Table 4.5. Experiment results (global ranking)†

Warehouse-1	Base scenario		Scenario-1	
Efficient subset	$N = 38$; 99.01‡		$N = 82$; 99.47	
	(c_2, s_4, b_2, r_4)	(c_3, s_2, b_2, r_4)	(c_3, s_2, b_2, r_4)	—
	(c_2, s_4, b_1, r_4)	(c_1, s_4, b_2, r_4)	—	—
2nd eff. subset	$N = 38$; 98.65		$N = 82$; 98.99	
	(c_3, s_4, b_1, r_4)	(c_3, s_4, b_2, r_4)	(c_3, s_2, b_1, r_4)	(c_3, s_4, b_2, r_4)
	(c_3, s_2, b_1, r_4)	—	(c_2, s_4, b_2, r_4)	(c_3, s_4, b_1, r_4)
	—	—	—	—
Warehouse-2	$N = 33$; 99.52		$N = 153$; 99.62	
Efficient subset	(c_3, s_2, b_1, r_1)	(c_3, s_2, b_2, r_1)	(c_3, s_2, b_2, r_1)	(c_3, s_2, b_1, r_1)
	—	—	—	—
2nd eff. subset	$N = 33$; 97.13		$N = 153$; 97.89	
	(c_3, s_2, b_1, r_4)	(c_3, s_2, b_2, r_4)	(c_3, s_2, b_2, r_4)	(c_3, s_2, b_1, r_4)
	(c_2, s_2, b_2, r_4)	(c_2, s_2, b_1, r_4)	—	—
	(c_3, s_4, b_1, r_4)	(c_2, s_2, b_2, r_1)	—	—
	(c_2, s_2, b_1, r_1)	(c_3, s_4, b_2, r_4)	—	—
Warehouse-3	$N = 17$; 99.38		$N = 118$; 99.80	
Efficient subset	(c_3, s_2, b_1, r_4)	(c_3, s_2, b_2, r_4)	(c_3, s_2, b_2, r_4)	(c_3, s_2, b_1, r_4)
	(c_3, s_2, b_2, r_4)	(c_3, s_2, b_1, r_4)	—	—
	—	—	—	—
2nd eff. subset	$N = 17$; 95.15		$N = 118$; 98.40	
	(c_2, s_4, b_2, r_4)	(c_2, s_2, b_1, r_4)	(c_3, s_4, b_2, r_4)	(c_3, s_4, b_1, r_4)
	(c_2, s_4, b_1, r_4)	(c_3, s_4, b_2, r_4)	(c_2, s_4, b_1, r_4)	—

† See Table 4.2 for notations.
‡ Number of replications (per policy set) and mean efficiency of the subset (%).

the efficient subset. For all warehouses, policy sets with larger capacities (24 and 48) are dominating. Much in line with our expectations, combined routing takes part in all efficient policy sets of warehouses-1 and 3. Policy s_2 has better performance than all other storage policies in almost all situations in warehouses-2 and 3. There is still no consensus about the superiority of two order sequencing policies considered in this chapter. We suspect that the distinct usefulness of the

Table 4.6. Experiment results (contd.)

	Scenario-2		Scenario-3	
Warehouse-1				
Efficient subset	$N = 11$; 99.54		$N = 39$, 99.33	
	(c_3, s_2, b_2, r_4)	(c_3, s_2, b_1, r_4)	(c_2, s_4, b_2, r_4)	—
	—	—	—	—
2nd eff. subset	$N = 11$; 98.54		$N = 39$; 98.69	
	(c_3, s_4, b_2, r_4)	(c_3, s_4, b_1, r_4)	(c_1, s_4, b_2, r_4)	(c_1, s_4, b_1, r_4)
	(c_3, s_2, b_2, r_1)	(c_3, s_2, b_1, r_1)	(c_3, s_2, b_2, r_4)	(c_3, s_4, b_2, r_4)
	—	—	(c_3, s_2, b_1, r_4)	—
Warehouse-2	$N = 16$; 99.03		$N = 62$; 99.34	
Efficient subset	(c_3, s_2, b_1, r_1)	(c_3, s_2, b_2, r_1)	(c_3, s_2, b_1, r_1)	(c_3, s_2, b_2, r_1)
	(c_3, s_2, b_2, r_4)	—	—	—
2nd eff. subset	$N = 16$; 97.96		$N = 62$; 97.46	
	(c_3, s_2, b_1, r_4)	—	(c_2, s_2, b_2, r_4)	(c_2, s_2, b_1, r_4)
	—	—	(c_3, s_2, b_1, r_4)	(c_2, s_2, b_2, r_1)
	—	—	—	—
	—	—	—	—
Warehouse-3	$N = 11$; 99.74		$N = 44$; 99.21	
Efficient subset	(c_3, s_2, b_1, r_4)	(c_3, s_2, b_2, r_4)	(c_3, s_2, b_2, r_4)	(c_3, s_2, b_1, r_4)
	—	—	(c_2, s_4, b_2, r_4)	(c_2, s_2, b_2, r_4)
	–	—	(c_2, s_4, b_1, r_4)	(c_2, s_2, b_1, r_4)
2nd eff. subset	$N = 11$; 97.91		$N = 44$; 97.89	
	(c_3, s_4, b_2, r_4)	(c_3, s_4, b_1, r_4)	(c_3, s_4, b_2, r_4)	—
	(c_2, s_4, b_2, r_4)	(c_2, s_4, b_1, r_4)	—	—

Earliest-Due-Date policy depends on the combined effect of several parameters, such as the relative magnitude of the due-date distribution, demand intensity, and the average make-span of picking tasks. An interesting observation is that S-shape routing (r_1) in most experiments outperforms combined routing (r_4) in warehouse-2. The reason for that is because, in the warehouse of fewer aisles, items are relatively denser in each aisle; so S-shape routing becomes more efficient.

4.4.2 Partial comparisons

Under practical constraints, warehouse managers may also want to know the relative performance among policy sets when one or more of the policy dimensions is fixed. The reason for this analysis is that, in practice, there may be occasions where certain policies cannot be modified due to the technology or practical constraints—partial comparisons provide decision support in this constrained environment. Managers can also compare the efficient subset with those obtained in the relaxed setup (e.g., Table 4.5) to justify the decision about adopting a new technology. In implementation, the fixed dimension can be treated as an unchanged parameter, and we can just examine those policy sets with the fixed parameter in our simulation results. Specifically, we are allowed to reduce the size of subset selection (m) while maintaining similar precision, and the partial comparisons can be conveniently done based on the simulation outputs obtained from the global comparisons (cf. Eqn. (4.4) and (4.5) in the appendix). Table 4.7 gives the results when we fix one dimension in the policy set ($m = 5$ is used).

4.4.3 Dimension-wise comparisons

Representing the results by individual policy dimensions can give further insight into the trade-offs between different policies. After grouping the efficiency scores by different types of policies, we can, for example, use box plots to display the tendencies of performances of different policy sets in that dimension. Figure 4.5 to Figure 4.8 give examples of the dimension-wise box plots for warehouse-1. These figures visualize some key characteristics of the performances (i.e., median and inter-quartile range) when adopting one specific policy in some policy dimension. For instance, Figure 4.5 shows that c_3 (capacity 48) has the highest median and the narrowest interquartile range. However, the figure also indicates that c_3 has many extremely inefficient outliers. Therefore, c_3 (48) seems to be "riskier" in the current warehouse environment because extreme values are more probable. Figure 4.7 indicates that the difference between the overall performance

Table 4.7. Experiment results for warehouse-1 ($m = 5$)

c fixed at c_1	Base scenario	Scenario-1	Scenario-2	Scenario-3
Efficient subset	98.8[†]	96.2	95.3	99.0
	(c_1, s_4, b_1, r_4)	(c_1, s_4, b_1, r_4)	(c_1, s_4, b_1, r_4)	(c_1, s_4, b_1, r_4)
	(c_1, s_4, b_2, r_4)	(c_1, s_4, b_2, r_4)	(c_1, s_4, b_2, r_4)	(c_1, s_4, b_2, r_4)
2ndly efficient subset	94.4	91.1	90.2	94.5
	(c_1, s_2, b_2, r_4)	(c_1, s_4, b_2, r_3)	(c_1, s_4, b_2, r_3)	(c_1, s_2, b_2, r_4)
	(c_1, s_2, b_1, r_4)	(c_1, s_4, b_1, r_3)	(c_1, s_4, b_1, r_3)	(c_1, s_2, b_1, r_4)
	(c_1, s_4, b_1, r_3)	(c_1, s_2, b_2, r_4)	(c_1, s_2, b_2, r_4)	(c_1, s_2, b_1, r_1)
b fixed at b_1	Base scenario	Scenario-1	Scenario-2	Scenario-3
Efficient subset	98.5	99.1	98.8	98.4
	(c_1, s_4, b_1, r_4)	(c_3, s_2, b_1, r_4)	(c_2, s_4, b_1, r_4)	(c_1, s_4, b_1, r_4)
	(c_2, s_2, b_1, r_1)	—	(c_3, s_2, b_1, r_1)	(c_3, s_2, b_1, r_4)
	(c_2, s_2, b_1, r_4)	—	(c_3, s_2, b_1, r_4)	(c_3, s_4, b_1, r_4)
	(c_2, s_4, b_1, r_4)	—	(c_3, s_4, b_1, r_4)	—
	(c_3, s_2, b_1, r_4)	—	—	—
2ndly efficient subset	—	98.2	96.8	97.5
	—	(c_3, s_2, b_1, r_1)	(c_2, s_2, b_1, r_4)	(c_2, s_2, b_1, r_1)
	—	—	—	(c_3, s_2, b_1, r_1)

[†] Mean efficiency of the subset (%).

of two order sequencing policies is only incremental. Figure 4.8 also matches the results in Table 4.5, in which combined routing is identified in all efficient policy sets of warehouse-1. Lastly, using the same approach, the warehouse manager can graphically juxtapose the results obtained from different scenarios to further investigate the robustness of certain policies.

4.4.4 Comparisons among systems

In Section 4.1, the efficiency rankings are derived separately for three warehouses (e.g., Table 4.5). Now, by comparing three warehouses of different shapes, we can examine the robustness of policy sets in different system parameters. Warehouse managers can now analyze the constitution of efficiencies when the shape of the

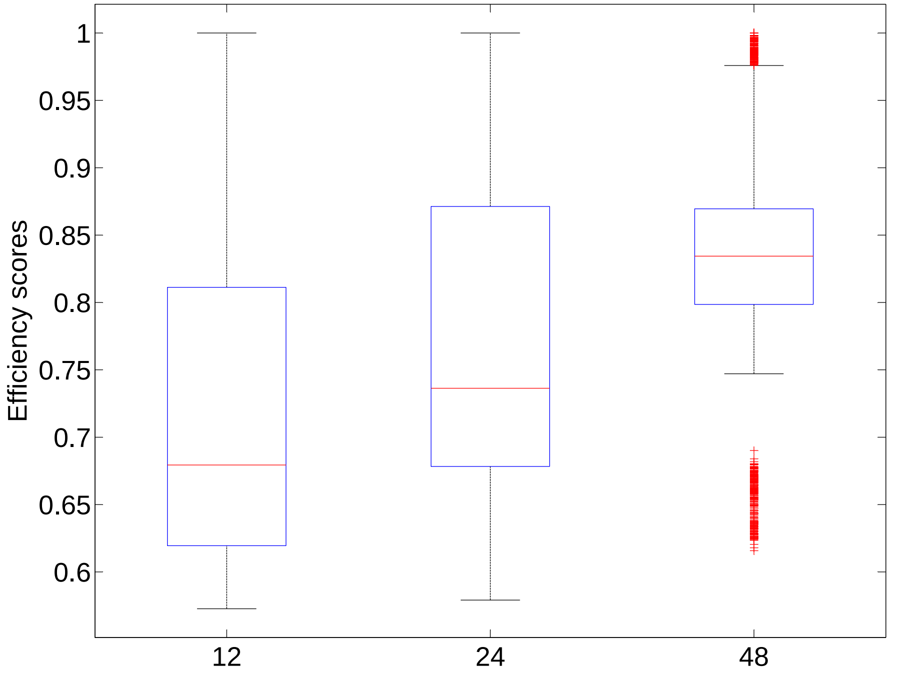


Fig. 4.5. Efficiencies of *capacities* in the base demand scenario

warehouse varies. This is done by reorganizing random samples of efficiencies of 120 policy sets in three warehouses; that is, we are now looking at 120*3 policy sets. Then we can simultaneously examine the performance of three warehouses, by clustering the joint samples by their originating warehouses. Consequently, the effects of different order picking policies on efficiencies can be evened out after aggregation, rendering warehouse shapes the only contributing factor. The efficiency scores of policy sets in three warehouses in the base scenario are graphically illustrated in Figure 4.9. It is clear that warehouse-3 outperforms the other two in the base scenario (high median efficiency with a small dispersion).

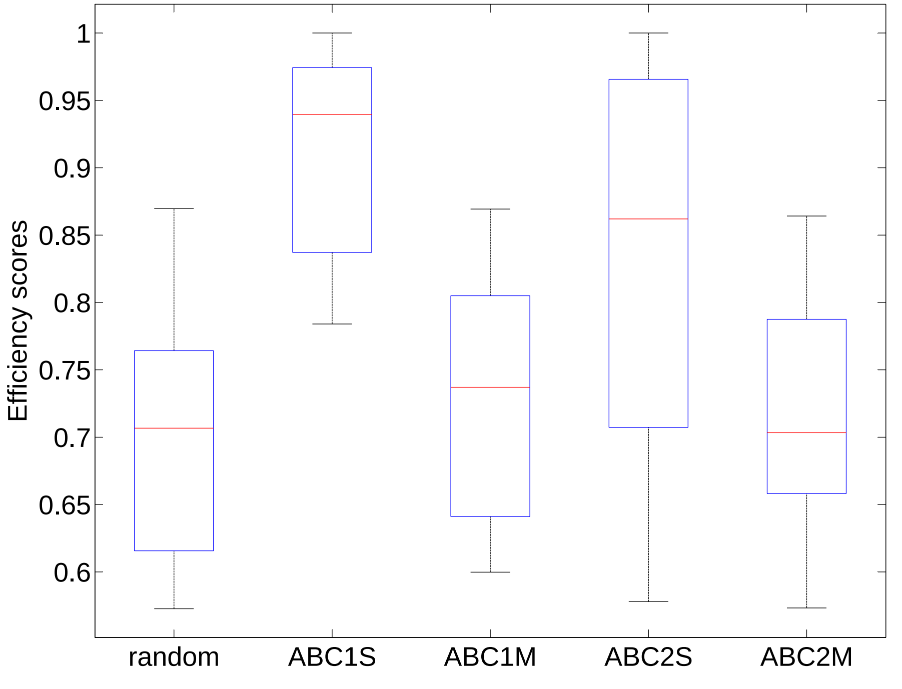


Fig. 4.6. Efficiencies of *storage policies* in the base scenario

Our experimental results listed in Table 4.5 can be summarized as follows. In warehouses-1 and 3, c_3 and r_4 appears in almost all efficient policy sets in the global ranking in all three scenarios (with the only exception of scenario 3 for warehouse-1). Therefore, it is advisable for these two warehouses to adopt these two policies in all expectations of increasing demand. In warehouse-2, c_3 and r_1 are clearly dominating. Table 4.5 and Figure 4.7 together signify that there is only minor difference between the performance of b_1 and b_2 in most situations. The storage policy s_2 is superior to s_4, especially in most high-demand scenarios. Figure 4.9 shows that warehouse-3 has a superior performance. Therefore, without

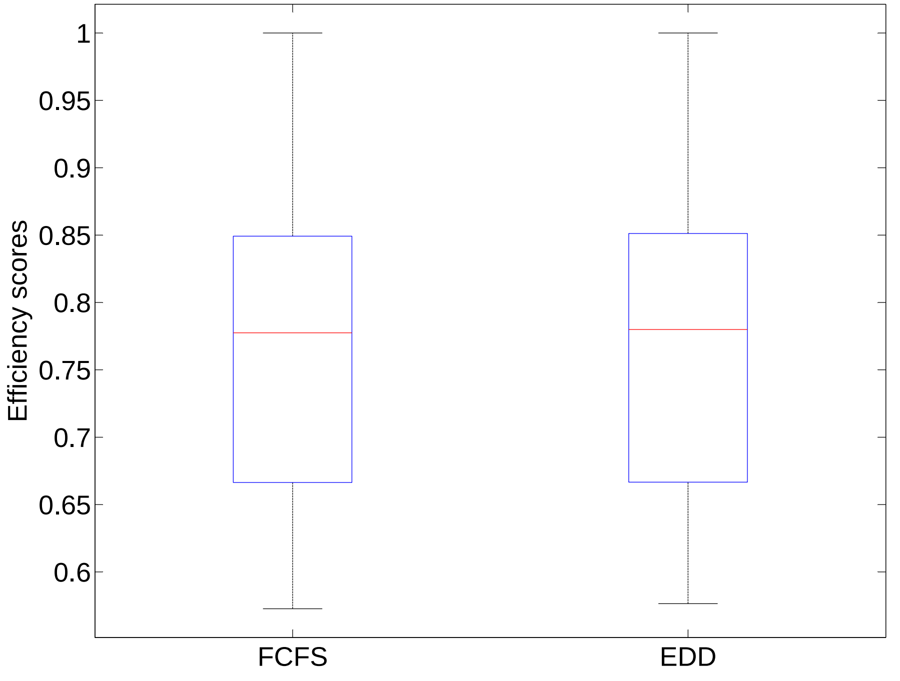


Fig. 4.7. Efficiencies of *order sequencing policies* in the base scenario

considering the costs of adaptation, the managers of warehouse-1 and warehouse-2 can consider rearranging their warehouses in a way similar to warehouse-3.

4.5 Conclusions and future directions

Order picking decisions, like many problems in supply chain management, are commonly characterized by multi-dimensionality: managers need to make several interrelated decisions simultaneously, while considering the trade-off among multiple performance attributes of the outcome. Existing approaches, however, tend to deal with each decision and criterion separately—this type of disintegrative

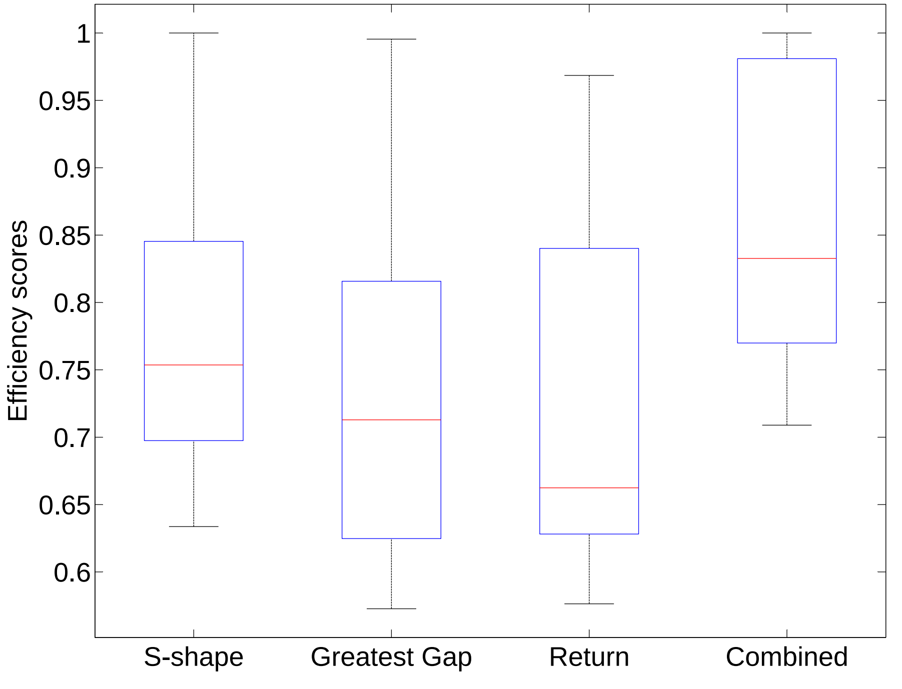


Fig. 4.8. Efficiencies of *routing policies* in the base scenario

approaches inevitably leads to sub-optimization and misunderstanding over the system. In this chapter, we propose a holistic framework that helps managers efficiently evaluate and select the ideal combination of order picking policies.

Our framework considers multiple criteria that a superior set of order picking policies should achieve: the ability and stability to process a large number of picking tasks with high service level and minimal costs, and we evaluate each policy set by its composite efficiency index. In the framework, we do not aim at identifying the single best policy set, which can be computationally consuming for large scale problems, and the most efficient policy set may not be the robust. Instead, we search for the group of superior policy sets, and allow managers to

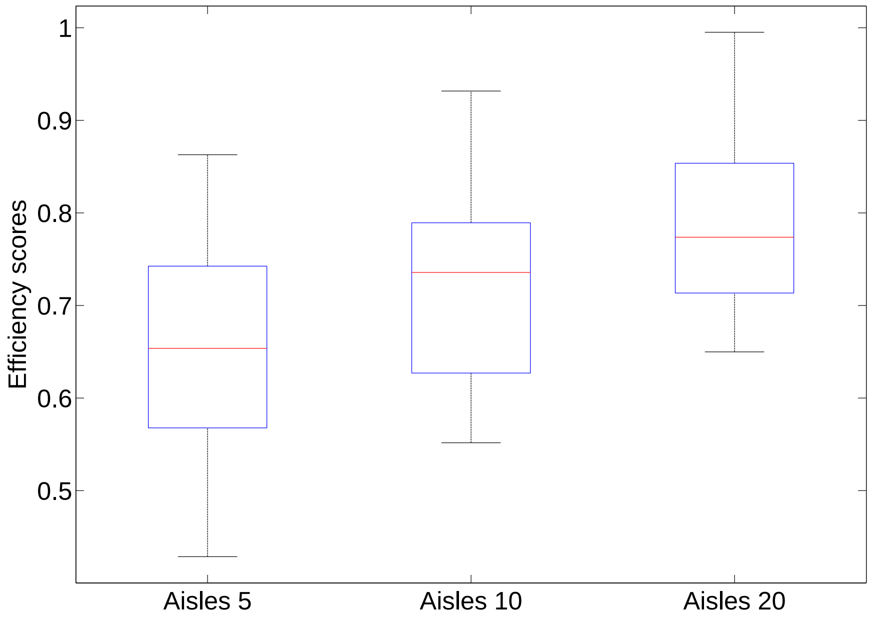


Fig. 4.9. Efficiencies of three warehouse shapes in the base scenario

participate in the final selection process. Warehouse managers can therefore select order picking policies with increased flexibility in the changing environment.

First, in addition to the examples presented in Section 4, our framework can also be applied to other problems in order picking systems. Some interesting directions include, but are not limited to, zoning with or without additional sorting time, comparing pick-and-pack with put systems, or addition of cross-aisles in the warehouse. In addition, warehouse managers are also recommended to apply the framework based on empirical data to gain further insight into current warehouse performances. Weight restrictions can be imposed on DEA models according to particular operational circumstances in warehouses. For instance, in logistic operations of important spare part components, since tardy deliveries may incur tremendous costs to both transactional parties, the service level objective may far outweigh the operational costs.

Appendix A: Koenig and Law's subset selection algorithm

In what follows we give a short introduction to the subset selection method developed in Koenig and Law (1985). In using this approach, we want to prescreen the m best out of total k policy sets. Formally,

$$P(\text{correct selection}) \geq P^*, \text{ given that } \mu^*_{[m]} - \mu^*_{[m+1]} \geq \delta^*, \tag{4.3}$$

where $\mu^*_{[1]} \geq \mu^*_{[2]} \cdots \geq \mu^*_{[k]}$ denote the ordered mean efficiencies from k independent normal distributions with unequal variances, and $\delta^* > 0$ denotes the indifference-zone width prescribed by the user. We now describe the stepwise procedure of subset selection.

STEP-1: The user predetermines (i) the number of pilot runs n ($n \geq 2$, preferably greater than 8), (ii) the size of the subset $m < k$, (iii) the selection probability P^*, and the indifference-zone width δ^*.

STEP-2: The total number of replications n_i for policy set i is derived from:

$$n_i = \max\Big\{n + 1, \lceil \hat{s}_i^2(n) * (h/\delta^*)^2 \rceil\Big\}, \tag{4.4}$$

where $\hat{s}_i^2(n)$ is the sample variance of policy set i obtained from n pilot runs and $\lceil a \rceil$ is defined to be the smallest integer greater than or equal to a; h is a positive number, whose value can be computed by numerically solving the equation:

$$P^* = g(h) = (k - m) \int_{-\infty}^{\infty} \Big(F(t + h)\Big)^m \Big(1 - F(t)\Big)^{k-2m} f(t)\, dt, \tag{4.5}$$

where f and F are the PDF and CDF of a t-distribution with $n-1$ degrees of freedom, respectively. It can be shown that, for arbitrary $h > 0$, (4.5) forms a non-trivial lower bound for the probability of a correct selection; i.e., $(k-m)!m!/k! \leq g(h) \leq P(\text{correct selection})$.

Since evaluating one policy set also requires the input/output information of other policy sets, we should execute $N = \max_i\{n_i\}$ replications for each policy set to satisfy (4.4).

STEP-3: We implement the second stage sampling by simulating $N-n$ replications.

STEP-4: Compute the weighted sample mean of policy set i, $i = 1, \ldots, k$, as

$$\hat{\theta}_i = w_{i1}\Big(\sum_{j=1}^{n} \theta^*_{ij}/n\Big) + \Big(1 - w_{i1}\Big)\Big(\sum_{j=n+1}^{N} \theta^*_{ij}/(N-n)\Big), \tag{4.6}$$

where θ^*_{ij} denotes the efficiency of policy set i obtained from the jth replication, and the weight to the first stage sampling w_{i1} is given by

$$w_{i1} = \frac{n}{N}\Big(1 + \sqrt{1 - \frac{N}{n}[1 - \frac{(N-n)}{\hat{s}^2_i(N)}(\frac{h}{\delta^*})^2]}\Big). \tag{4.7}$$

STEP-5: The best m policy sets can now be determined by observing $\hat{\theta}_{[1]}, \hat{\theta}_{[2]}, \ldots, \hat{\theta}_{[m]}$, where $\hat{\theta}_{[1]} \geq \hat{\theta}_{[2]} \geq \ldots \geq \hat{\theta}_{[m]}$.

Appendix B: Tukey's method

Tukey's method compares pairs of policy sets k and j by constructing simultaneous confidence intervals based on the studentized range distribution:

$$Q = \frac{\max_{r \in P}\{\bar{X}_r(n_r)\} - \min_{r \in P}\{\bar{X}_r(n_r)\}}{\sqrt{\mathrm{MSE}(1/n_k + 1/n_j)/2}}, \tag{4.8}$$

where $\bar{X}_r(n_r)$ stands for the sample mean efficiency of policy r based on n_r random samples, and MSE denotes mean square error (note that n_r has been determined in the subset selection procedure).

By Eqn. (4.8), we can construct a test statistic $Q_\alpha(m, df)$, which corresponds to the upper α percentile of Q with m comparison groups and df degrees of freedom associated with MSE. Then it holds with probability $1 - \alpha$ that

$$\max_{r \in P}\{\bar{X}_r(n_r)\} - \min_{r \in P}\{\bar{X}_r(n_r)\} \leq Q_\alpha(m, df)\sqrt{\mathrm{MSE}(1/n_k + 1/n_j)/2}. \tag{4.9}$$

By the construction of (4.9), it follows with the same probability that

$$\mu_k^* - \mu_j^* \in \left(\bar{X}_k(n_k) - \bar{X}_j n_j) \pm Q_\alpha(m, df)\sqrt{\mathrm{MSE}(1/n_k + 1/n_j)/2}\right), \text{ for all } k \neq j. \tag{4.10}$$

5

Resource allocation by bootstrapping efficiency estimates in the uncertain environment

In the previous chapter, we developed a methodology to design processes in situations where environmental uncertainties can be represented as known stochastic processes. In this chapter, we turn to another class of situations, where we cannot pre-specify these probability distributions. Instead, design decisions are made based on one observation of the anticipated performance of available designs. In this chapter, I develop bootstrap algorithms to approximate the efficiency distributions of different system's design specifications, as well as a model for resource allocation to different designs. We exemplify the approach by applications to R&D project selection and budgeting problems in a supply chain. Finally, as the bootstrap DEA distributions are mostly non-normal, we propose a normalization procedure for the bootstrap efficiency distributions. By applying this method, we can accommodate the bootstrap distributions to a variety of statistical techniques that assume a normal distribution assumption.

5.1 Introduction

Firms in today's market are faced with increasing pressure to respond to market changes and potential problems in realtime. This situation not only induces more frequent product introductions and technology advance, but also shortened live cycles for products and information (Petrin, 2002). Constant product innovation and rapid introductions necessitate fast decision-making and planning under a high level of uncertainty; Bourgeois and Eisenhardt (1988) find that in the high-velocity environment (for example in the computer industry), the incessantly changing market can make information inaccurate, unavailable or obsolete. Design processes in this situation are often difficult, because managers need to be predict system's performance with different design parameters, while only limited information is available for decision-making.

One popular way to deal with decision-making under uncertainty is to use methods based on Monte-Carlo simulation, in which known uncertain factors in the environment are represented by values generated by computer simulation, and the goal is to approximate statistics of interest. However, in the high-velocity, complex, or unstable environment, it might not always be straightforward to prescribe probability distributions for these uncertain factors. For example, specifying the distribution of the demand pattern of a new product can be very difficult or subjective. The need for frequent re-designs and fast decisions further eliminate the possibility to conduct a large-scale and comprehensive survey and experiment.

In this chapter, we deal with one class of decision problems often seen in the "high-velocity" environment. In these problems, we have only one observation (or estimation) of the inputs and outputs of decision alternatives. Our aim is to distribute limited resources among available options. The decision-making process is considered to be a two-step "evaluate-then-decide" process. For instance, we rank different designs according to certain criteria first, and then select the best or the best few designs. A firm may have many parallel projects competing in the new product development, and each project is characterized by its estimated contribution (e.g., sales, market share, patterns) and required resources (e.g., man-power, equipments). Managers will select projects for execution based on the resource constraint or output target; e.g., the amount of resources available, or a good level of confidence that sales figure will exceed a certain threshold.

As design problems concern with multiple factors, the process design approach should be able to take that into consideration. In addition, the ideal design approach should also reveal the level of risks (i.e, variation of performance) to the decision-maker, since a large amount of investments is usually associated with these decisions and hence they are decisive for a firm's and supply chain's future market position.

In this chapter we focus on the resource allocation problem in this high-velocity environment. We develop a new methodology that consists of an improved bootstrap algorithms of Data Envelopment Analysis (DEA) and a mean-variance allocation model. As noted in previous chapters, DEA is a nonparametric approach to measure relative efficiencies of systems that use multiple inputs to produce multiple outputs. The statistical properties of DEA provide a basis for the development of bootstrap algorithms (Coelli, 2005).

The main contribution of this chapter is twofold. First, we propose a decision model in connection with the bootstrap analysis, such that the bootstrap information can be transformed into decision-support information. Specifically, although the first DEA bootstrap algorithm has been proposed by Simar and Wilson (1998) (hereafter SW), so far we did not find any empirical applications of SW's algorithm in the literature. This may be due to the fact that the efficiency bootstrap distributions per se are not explanatory in how they can add to decision-making. Moreover, SW did not tout the way to tap into the DEA bootstrap outputs.

We bridge the gap by proposing a hybrid approach that maps bootstrap outcomes to efficient allocation portfolios. Second, we will show that the bootstrap approach based on DEA (e.g., SW's) will exhibit exceptionally volatile estimates for certain efficient units. Later in this chapter we will show that this drawback could distort information regarding the relative performance of evaluated units, especially when we consider the performance risks. To rectify this problem, we develop an alternative efficiency measurement model, as well as its bootstrap algorithm. We will show that our new model has the same merits of the DEA model, yet it is free from the undesirable sensitivity property manifested in the bootstrap results. Our methodology is applied to an empirical R&D project selection and budgeting problem, where the resource allocation is taken based on stated budget requirements and expected contributions. We also present an application of the batch-mean algorithm to transforming the bootstrap distributions into normal ones; this normalization algorithm can be used in situations where the second phase of the analysis (in our case, the mean-variance model) requires a normality assumption on the underlying distributions.

The remainder of this chapter will proceed as follows. In Sec. 5.2, we discuss the statistical background of the DEA model and the bootstrap method. We elaborate on the probability models and bootstrap algorithms constructed based on the modified cross-efficiency method in Sec. 5.3. In Sec. 5.4, the distinction between these two models is compared. In Sec. 5.5, we apply the mean-variance formulation to the bootstrap distributions to find out the mean-variance efficient allocation portfolios; we also analyze the mean-variance trade-off of allocation portfolios. In Sec. 5.6, we use batch means and the method of multiple statistical testings to develop a normalization algorithm for the bootstrap distributions. In the final section we provide a summary of this chapter.

5.2 Statistical properties of DEA models and bootstrap theories

In spite of its mathematical appearance, DEA can be regarded as an efficiency estimator and has its own statistical properties. These properties are essential for the development of DEA bootstrap approaches. In this section we review the statistical aspects of DEA efficiency measurement; this is followed by a brief introduction to the bootstrap theory.

5.2.1 A statistical view of DEA models

In the previous chapters we calculate efficiency scores of firms as if we are just solving optimization problems. In fact, the DEA efficiency is closely related to production economics. Over the years, various econometrics methods, whether parametric or nonparametric, have been developed to estimate efficiency in different contexts where different assumptions are needed. Specifically, the DEA model can also be regarded as a nonparametric efficiency estimator. The efficiency estimates obtained from DEA depend closely on its nonparametric estimate of the unknown production function; yet the production frontier estimate of DEA is susceptible to finite sample errors and sampling variation (Kneip et al, 1998; Simar and Wilson, 1999). Therefore an understanding of the statistical properties of the efficiency estimates can shed further light on the precision and confidence of the evaluation results. We begin this section by reviewing the statistical aspects of DEA, and then we will introduce bootstrap methods and its application to DEA. In this chapter, we will utilize bootstrapping method to assess the stability of DEA estimates.

The development of DEA as an efficiency estimator stems from conventional production economics (Coelli, 2005). In this framework, we draw samples to estimate the relation between production inputs and outputs, which we call a *production function*. Subsequently, we can deduce the technical inefficiency of firms by comparing the sampled firms with the production function. As such, DEA provides a nonparametric and piecewise linear estimation of the production function. Banker (1993) is the pioneering work that explores the statistical properties of DEA. He proves the consistency of DEA in the univariate case (single input with multiple outputs) for arbitrary concave and monotone production functions. He also proposes an asymptotic test procedure for statistical inferences on efficiencies estimated by DEA models (see also Banker and Chang (1995) for a comparison between different testing methods). Korostelev et al (1995) and Kneip et al (1998) derive the convergence rate of DEA estimators in more general settings. They show that, under a fixed sample size, the convergence rate decreases exponentially as the number of input/output variables increase.

We have reviewed some aspects of DEA as an efficiency estimator. Only with this statistical interpretation can we proceed to develop bootstrap algorithms for DEA. So how exactly does bootstrap work? we will next give a primer on bootstrap theories, and briefly review prior bootstrap approaches in the literature.

5.2.2 Bootstrap preliminaries

A primary goal in statistical inference is to infer about parameters of a population F_0 by drawing random samples. To do this, we need information about the sampling distribution of an appropriate statistic (or *estimator*). Sampling distributions, however, rely heavily on both population F_0 and the mathematical structure of the estimator. Therefore, only under special assumptions about F_0 can we give the analytical description of the sampling distributions of certain estimators. This would impose great restrictions on the applicability of statistical analysis in many real-world problems.

Bootstrapping is a collection of computational methods to approximate sampling distributions by resampling the obtained sample. For more details about the bootstrapping approach, Efron and Tibshirani (1993) is the classic introduction to the subject; Hall (1992) gives a comprehensive theoretical treatment of bootstrap theories. Below I outline the bootstrap principle for nonparametric problems.

The main use of bootstrapping is to approximate sampling distributions that cannot be analytically represented. The basic principle is to use the observed sample as an estimate of the population of interest[1]. We can therefore draw bootstrap samples repetitively from the estimated population to approximate the sampling distribution of interest.

The way in which we construct the estimated population will determine the bootstrap to be parametric or nonparametric. In parametric bootstrap methods, the obtained sample will be used to estimate the parameters associated with the predetermined probability distribution. Bootstrap samples are then drawn

[1] Efron and Tibshirani (1993) contrast the true population and the estimated population by referring them as the "real world" and "bootstrap world," respectively; Hall (1992) vividly exemplifies the two populations by Russian matryoshka dolls.

from the distribution given the estimated parameters. Nonparametric bootstrap methods, on the other hand, do not make distributional assumptions, and will be introduced next.

Let $(x_1, x_2, \ldots, x_n)$ be a random sample drawn from the unknown F_0, namely

$$(x_1, x_2, \ldots, x_n) \overset{\text{iid}}{\sim} F_0. \tag{5.1}$$

In the nonparametric method, F_1 represents the empirical distribution of the sample of size n drawn from F_0. Specifically, F_1 is constructed by allocating $1/n$ probability mass to each x_i in the random sample.

Let $(x_1^*, x_2^*, \ldots, x_n^*)$ represent a random sample from F_1:

$$(x_1^*, x_2^*, \ldots, x_n^*) \overset{\text{iid}}{\sim} F_1. \tag{5.2}$$

By sampling from F_1, we can obtain the bootstrap distribution of the estimator of interest g^2. The relation resultant distribution F_2 represents an approximation to the sampling distribution given F_0.

The bootstrap principle refers to the assumption that the relationship between F_1 and F_2 is a close resemblance to the relation between F_0 and F_1. Since we have full knowledge of the empirical distribution from the sample, we can use Monte Carlo simulation to approximate F_2 based on F_1.

We use an example in Efron and Tibshirani (1993) to illustrate the usage of the bootstrap method. A common usage of bootstrap is for the estimation of standard errors. Standard errors are classically used to indicate the accuracy of a summary statistic. To estimate the standard error of the sample correlation coefficient $\hat{\rho}(x, y)$ between two random variables x and y, however, we often assume that (x, y) are bi-normally distributed under this assumption. Then an estimate of the standard error of $\rho(x, y)$ can be given by

[2] See Efron and Tibshirani (1993) for suggestions about the appropriate values of B for different purposes of bootstrapping.

$$\hat{\sigma}(\hat{\rho}(x,y)) = (1 - \hat{\rho}(x,y)^2)/(n-3), \tag{5.3}$$

where n denotes the sample size.

Eqn. (5.3) works well if the the distribution is close to bi-normal, but would become questionable otherwise. In fact, deriving a closed-form approximation to an estimate of standard errors can become extremely difficult, if not impossible, when the distribution does not have nice analytical properties (such as normal distributions in the above assumption), or when the summary statistic grows in complexity. The theory and method of bootstrapping provide an easy way out—we can simply resample the data and derive the bootstrap approximated value of $\hat{\sigma}$, regardless the true distribution of $\hat{\sigma}$.

Simar and Wilson (1998) (hereafter SW) first developed the bootstrap algorithm of the BCC DEA model (Banker et al, 1984). Based on a single sample of input and output variables, their method can be used to approximate the true efficiency distributions of all evaluated units. The SW approach enables us to assess the variability of efficiency in a general multi-inputs and multi-output situation.

SW use a nonparametric smoothed bootstrap method to approximate the sampling distribution of DEA efficiency estimates. Simar and Wilson (1999) later develop a similar bootstrap method for the Malmquist productivity index. Simar and Wilson (2000) provide an overview about recent developments of the statistical analysis of DEA.

5.3 Mathematical formulations

In this section we first introduce the formulation and interpretation of the DEA multiplier model. The multiplier model will serve as the basis for us to develop the new efficiency index, as well as its probability model and bootstrap algorithm.

5.3.1 The DEA multiplier model

Most production processes involve multiple production factors. A customary approach to evaluate multi-factor processes is to assign weights to each factor, and hence the we can aggregate multiple factors into a single index. In situations where such universally accepted weights are unavailable[3], as often is the case in practice, we are then incapable of distinguishing true inefficiency from the effect of weight specifications (Cooper et al, 2006). DEA resolves this problem by allowing each evaluated unit to select weights that optimize its efficiency score, and therefore eliminates the influence of weight specifications on the evaluation results.

Formally, suppose n decision-making units (DMUs) are under evaluation. We denote the inputs and outputs used by DMU k as $X_k = [X_{k1}, \ldots, X_{ki}]$ and $Y_k = [Y_{k1}, \ldots, Y_{kj}]$, respectively. The input-oriented CCR efficiency (for DMU-1) is defined to be the optimal value of the fractional linear problem (Charnes et al, 1978):

$$\max \sum_{q=1}^{j} \mu_{1q} Y_{1q} \Big/ \sum_{p=1}^{i} \nu_{1p} X_{1p} \tag{5.4a}$$

$$\text{subject to } \sum_{q=1}^{j} \mu_{1q} Y_{kq} - \sum_{p=1}^{i} \nu_{1p} X_{kp} \leq 0,\ k = 1, \ldots, n, \tag{5.4b}$$

$$\mu_{1q}, \nu_{1p} \geq 0,\ p = 1, \ldots, i, \text{ and } q = 1, \ldots, j. \tag{5.4c}$$

Problem (5.4) is called the "multiplier" DEA model in the literature, because the decision variables are the multipliers attached the input and output variables. The objective function (5.4) is the weighted ratio of output and input factors, which conforms exactly to the classical definition of productivity. Problem (5.4) will maximize the evaluated DMU's efficiency by choosing some nonnegative weights ν_{1p}'s and μ_{1q}'s. The value of ν_{1p} and μ_{1q} can be interpreted

[3] One can think of these weights as the unit prices of productive factors. As such, it can be expected that "universally accepted weights," just like price information, are not always available.

as the relative importance of the variables in the evaluation process. Constraint (5.4b) ensures that the efficiency scores of any DMU will not be larger than one.

By normalizing the denominator of (5.4a), we can obtain an LP equivalent to (5.4)[4]:

$$\max \theta_1 = \sum_{q=1}^{j} \mu_{1q} Y_{1q} \tag{5.5a}$$

$$\text{subject to} \quad \sum_{p=1}^{i} \nu_{1p} X_{1p} = 1, \tag{5.5b}$$

$$\sum_{q=1}^{j} \mu_{1q} Y_{kq} - \sum_{p=1}^{i} \nu_{1p} X_{kp} \leq 0, \; k = 1, \ldots, n, \tag{5.5c}$$

$$\mu_{1q}, \nu_{1p} \geq 0, \; p = 1, \ldots, i, \text{ and } q = 1, \ldots, j. \tag{5.5d}$$

The evaluation process completes after we repeatedly solve problem (5.5) for the n individual DMUs. DMUs that obtain an efficiency score of one are called *efficient*, and *inefficient* otherwise. More specifically, a DMU is efficient when there exists a weight vector that makes its efficiency score equal to one, while other's scores do not exceed one.

5.3.2 The proposed method

In this section we propose a new efficiency index and its bootstrap algorithm. The new index has a similar structure with that of the DEA Cross-Efficiency (CE) index, hence the name "Revised Cross-Efficiency" (RCE). A detailed introduction to the DEA CE approach can be found in Appendix A, where we also present the bootstrap algorithm for the CE method. Here we provide a sketch of the CE approach. Roughly speaking, the CE approach is similar to the DEA multiplier

[4] Note that the problem is the dual formulation of the "radial" DEA model introduced in the preceding chapters.

model, in that we still solve (5.5) repetitively to obtain all optimal weight vectors[5]. The main difference between the CE and conventional DEA models is that, in the former a firm's efficiency is a function of all optimal weight vectors (including its own and others'), while in the latter approach efficiency depends on weights from the evaluated unit's multiplier model.

As discussed, the CE method operates in parallel with the multiplier DEA model, which is sensitive to variations of the extremely efficient DMUs (see Zhu, 2001). In the numerical results shown later, we will see evidence that both the bootstrap CE and DEA distributions of efficient DMUs have exceptionally wide spreads. We will also show that our RCE approach can circumvent this problem but still retain the merit of the CE method: better discrimination and a democratic evaluation scheme (i.e., considering optimal weights of all DMUs).

Revised cross-efficiency index (RCE): definition

In the CE method, the efficiency score is computed as an average of the self- and peer-evaluations scores. Further, according to (5.4a) these evaluation scores are a function of the self- and peer-evaluations weights. The RCE score is defined based on a similar principle, but instead we look at the hypothesized mean weights:

$$\mathrm{RCE}_k(F_0) = \sum_{q=1}^{j} \mathbb{E}\left\{\mu_q\right\} Y_{kq} \Big/ \sum_{p=1}^{i} \mathbb{E}\left\{\nu_p\right\} X_{kp}, \tag{5.6}$$

where μ_q, ν_p are the weight distributions with respect to input p and output q; X_{kp}, Y_{kq} are known input and output levels, respectively. It is easy to show that, just like the DEA and CE score, the RCE score is bounded between 0 and 1, and the score is be less than or equal to the DEA score θ_k. In (5.6), the efficiency score is determined as the ratio of the virtual input to virtual output (5.4a), which is similar to (5.16).

---

[5] Although we need to resort to an auxiliary procedure to obtain unique optimal weights; see Appendix A for more details.

Suppose that input weight distributions are independent of output weight distributions. An unbiased estimator of the RCE based on a size n sample is given as

$$\overline{\mathrm{RCE}}_k(F_0) = \sum_{q=1}^{j} \hat{\bar{\mu}}_q^* Y_{kq} \Big/ \sum_{p=1}^{i} \hat{\bar{\nu}}_p^* X_{kp}, \tag{5.7}$$

where $\hat{\bar{\mu}}_q^*$ and $\hat{\bar{\nu}}_p^*$ are the estimates of $\bar{\mu}_q^*$ and $\bar{\nu}_p^*$, respectively.

5.3.3 Probability model and bootstrap algorithm

The RCE (5.7) is a function of the random sample, and therefore a *statistic*. Next we will proceed to construct the probability mechanism behind it. Consider n DMUs are now under evaluation, and for each evaluated DMU, $n-1$ other DMUs are randomly drawn from an unknown population F_0. Then for the evaluated DMU, the DEA model produces n weight vectors $(\hat{\boldsymbol{\omega}}_1, \ldots, \hat{\boldsymbol{\omega}}_n)$, where $\hat{\boldsymbol{\omega}}_k = (\hat{\nu}_{k1}, \ldots, \hat{\nu}_{ki}, \hat{\mu}_{k1}, \ldots, \hat{\mu}_{kj})$, for $k = 1, \ldots, n$. A straightforward estimator for the mean weight vector is the sample mean:

$$\begin{aligned} \bar{\boldsymbol{\omega}} &= \sum_{k=1}^{n} \hat{\boldsymbol{\omega}}_k / n = (\bar{\nu}_{k1}, \ldots, \bar{\nu}_{ki}, \bar{\mu}_{k1}, \ldots, \bar{\mu}_{kj}), \\ &\text{where } \bar{\nu}_q = \sum_{k=1}^{n} \hat{\nu}_q / n, \ \bar{\mu}_q = \sum_{k=1}^{n} \hat{\mu}_q / n. \end{aligned} \tag{5.8}$$

Eqn. (5.8) leads to a plug-in estimator of RCE efficiency:

$$\widehat{\mathrm{RCE}}_k = \frac{\sum_{q=1}^{j} \bar{\mu}_q Y_{kq}}{\sum_{p=1}^{i} \bar{\nu}_p X_{kp}} = \frac{\sum_{q=1}^{j} \sum_{k=1}^{n} \hat{\mu}_{kq} Y_{kq}}{\sum_{p=1}^{i} \sum_{k=1}^{n} \hat{\nu}_{kp} X_{kp}}. \tag{5.9}$$

Denote the probability distribution of $\boldsymbol{\omega}_k$ by F_0. Since F_0 is unknown, we can estimate F_0 by its empirical distribution F_1; we achieve this by assigning probability mass $1/n$ on $\hat{\boldsymbol{\omega}}_k$ for $k = 1$ to n.

Given F_1, we can generate bootstrap samples of weight vectors:

$$F_1 \rightarrow (\hat{\boldsymbol{\omega}}_1^*, \hat{\boldsymbol{\omega}}_2^*, \ldots, \hat{\boldsymbol{\omega}}_n^*). \tag{5.10}$$

Based on the bootstrap samples we can calculate $\bar{\boldsymbol{\omega}}^*$ and $\widehat{\mathrm{RCE}}_k^*$ according to (5.8) and (5.10). By repeating this procedure, we obtain the bootstrap distribution of $\widehat{\mathrm{RCE}}_k^*$, for all DMUs $k = 1$ to n. We summarize the above procedure in Algorithm 2.

Algorithm 2 RCE bootstrap algorithm

1: estimate the weight vectors $(\hat{\boldsymbol{\omega}}_1, \hat{\boldsymbol{\omega}}_2, \ldots, \hat{\boldsymbol{\omega}}_n)$ by using model (5.5) and (5.17).
2: **for** $b = 1$ to B **do**
3:     **for** DMU $k = 1$ to n **do**
4:         sample with replacement from the empirical weight vectors $\hat{\boldsymbol{\omega}}_{b1}^*, \hat{\boldsymbol{\omega}}_{b2}^*, \ldots, \hat{\boldsymbol{\omega}}_{bn}^*$.
5:         obtain a bootstrap sample $\bar{\boldsymbol{\omega}}_b^* = n^{-1} \sum_{k=1}^{n} \boldsymbol{\omega}_{bd}^*$ for $d = 1, \ldots, n$.
6:         compute $\widehat{\mathrm{RCE}}_{kb}^*$ according to Eqn. (5.9).
7:     **end for**
8: **end for**

In the algorithm, we first compute an estimate of the weight vector from the DEA cross-efficiency model; then the weight vector is used to construct the empirical weight distributions. In STEPs 2–7, we resample from the empirical distributions for B times and obtain the bootstrap distributions of the RCE scores, where B is a user-specified parameter.

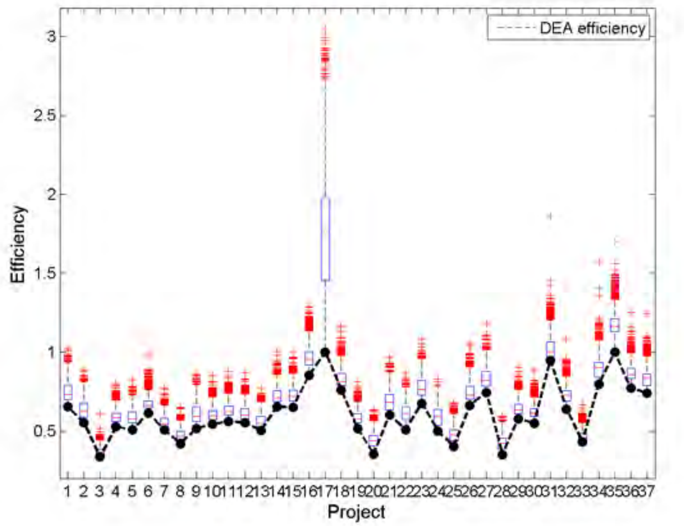
It is worth mentioning that the RCE bootstrap method is computationally more efficient than SW's and the CE bootstrap methods (see Alg. 5 in Appendix A), although these two approaches are constructed based on different efficiency models. This computational advantage comes from the fact that computing RCE only requires a few algebraic operations as shown in (5.9), as compared to solving multiple LP models for the SE and CE algorithms.

We have developed the bootstrap algorithms based on different definitions of cross-efficiencies. In the next section, we will put the new and existing bootstrap algorithms to test via a project selection problem. Our main points of interest are to empirically examine the sensitivity of SW's approach, and to see how our new approach performs by comparison.

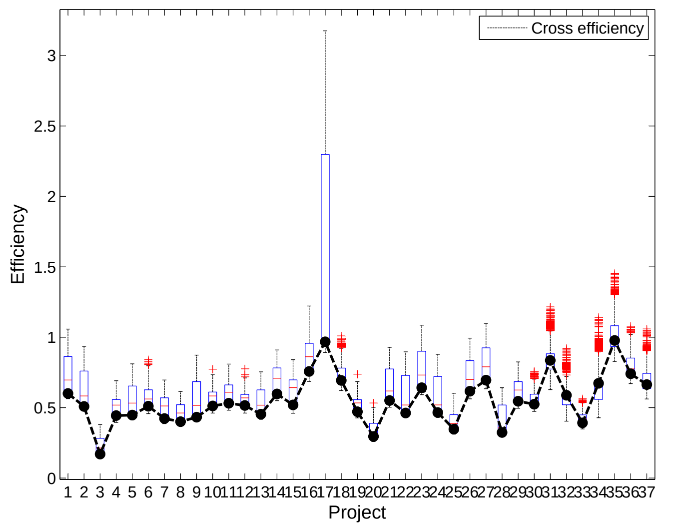
5.4 Empirical examination of bootstrap approaches

In this section we will illustrate the sensitivity issue of other DEA bootstrap approaches. Specifically, we will apply the SW and CE bootstrap algorithms to an empirical data set, which consist of 37 R&D project proposals in the iron and steel industry of Turkey. The data first appeared in Oral et al (1991) (see Tables 5.2 in Appendix B). Each project requires a budget to produce five outputs in terms of different aspects of contributions. Our objective is to evaluate project performance based on the project's required resources and intended contribution put forward in the project proposal. How the measurement or quantification of contributions of projects has been done may seem fuzzy; yet as we argued earlier, one of our main objectives is to facilitate decisions in this type of uncertain and high velocity environments. Thus we will use the data as an example in the remainder of this chapter, at least for an illustrative purpose.

Figure 5.1 displays the bootstrap results by boxplots. The scores derived from the DEA CCR model (5.4) and the CE method are also marked in the figures. In particular, Figure 5.1 shows that the bootstrap distributions of Project 17 from both algorithms show substantial variations. The reason is that Project 17 is *extremely efficient* in the DEA evaluation, which means that its input/output pair cannot be represented as a convex combination of other remaining projects and therefore the efficiency estimates will be sensitive to data variations; see Andersen and Petersen (1993) and Lovell and Rouse (2003) for a pertinent discussion



(a) Simar and Wilson's bootstrap algorithm



(b) The CE bootstrap algorithm (see Appendix A)

Fig. 5.1. Bootstrap distributions of project efficiencies

on the super-efficiency DEA model[6]. This sensitivity can be a serious drawback in practice. For instance, such extremely efficient DMUs may be considered unfavorable if we see variations in efficiency as an important evaluation criterion. Extremely efficient DMUs, however, at least weakly dominate all the other units in the deterministic sense. As such, the sensitivity of these two algorithms can distort our understanding of the relative performance of DMUs.

Another side observation is that the SW algorithm tends to produce more upward outliers (i.e., the + signs in the figure), as compared to the CE algorithm. The reason might be that, in the CE method, the influence of having extreme bootstrap samples will be averaged out by the CE formulation (5.16). Yet the effect of CE formulation, unlike the RCE one, is not enough to compensate that of the extremely efficient DMU.

In contrast, we can see from Figure (5.2), the RCE counterpart is more stable, and for all other projects the bootstrap distributions can reasonably follow the movement of CE and DEA scores. The stability is created by our specification of the probability model. More specifically, the empirical distributions of weights along with the RCE estimator are less volatile in estimation than bootstrapping the DMUs in the sample, as the SW and CE algorithms do.

Figure 5.1 also demonstrates that the DEA score dominates the RCE score. This domination arises from the definition of RCE scores (5.6). We also have an interesting observation that the median and mean of bootstrap RCE scores are close to the CE scores[7]. This also implies a fair degree of symmetry of the bootstrap distributions, as can be seen from Figure 5.1. Thus, based on the probabilistic structure of weights, the distributions of bootstrap RCE scores symmetrically encompass the CE scores. Also RCE scores are in general less susceptible to the finite sample error, as compared to the CE scores; see Figure 5.1 and the

[6] In fact, there are steps in the SW and Alg. 5 that correspond to a variant of the super-efficiency model.

[7] The average absolute deviation between the median and the CE score is 0.0136, while for the mean is 0.0011.

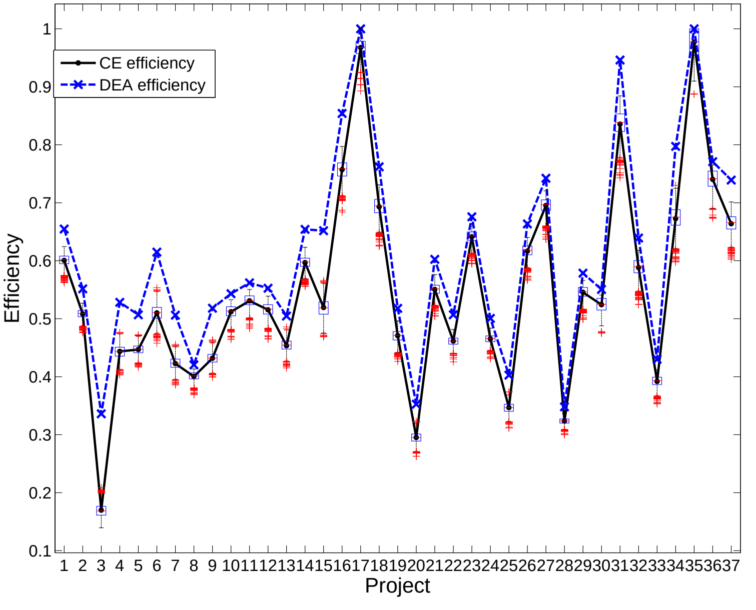


Fig. 5.2. Bootstrap outputs from Algorithm 2

discussion in the previous paragraph. Finally, we can also see that the CE scores do not dominate the associated DEA scores.

In conclusion, the RCE algorithm does not have the sensitivity problem of the SW and CE algorithms, while it can still capture the efficiency performance of evaluated units. In the next section, we will utilize the bootstrap result via the mean-variance formulation to determine resource allocations among R&D projects.

5.5 Application 1: R&D project selection and budgeting

To gain the first-mover advantage in a new market, product managers need to determine the new product portfolio and the related production planning before their competitors enter the market. The product portfolio decision is usually based on projected costs, demand, and expected profits within the product life-time. Estimating these figures is particularly difficult for products that are new to the market and the company. To earn competitive advantages, firms across different sectors have to allocate limited resources to R&D projects according to the estimated project performance and required budget. Purchasing managers responsible for procuring new materials or products can only rely on limited data to select ideal suppliers. Decision makers in the above situations all need a systematic approach to evaluate product lines, products, or suppliers. Building an *a priori* probabilistic model about the risk involved can be difficult due to the lack of information, and erroneous decisions can give rise to huge financial loss. In face of the such uncertainty and substantial consequences, the evaluation process in these decision problems should be comprehensive and objective, and the results should be justifiable to all stakeholders, who may have their own viewpoints about the relative importance associated with each evaluation criterion.

Decision problems of this class have several typical characteristics. First, limited or no data, or no information are available. These situations are often coupled with limited or no data available for decision support, due to shorten product life cycles and market's pressing demand for more product innovation. Second, decisions concern with multiple performance indications of the process, as discussed above. Third, since results of project development can have a major impact on the firm, it is important for consider the project risk factor in the selection process (Huchzermeier and Loch, 2001). As a first step to evaluate the performance risk, we need to obtain probability distributions of the statistic of interest. Several studies have used the cross-efficiency method in project evaluation and selection (Oral et al, 1991; Green et al, 1996; Beasley, 2003; Liang et al, 2008b). However, the CE method can only provide a point estimate of the CE score, and there seems no obvious evidence that can lead us to the usual parametric structure.

Our problem of project selections consists of the data of 37 independent projects, which were also used in the previous section. In addition to evaluating project performance, we also need to allocate limited resources to the selected projects. The resource allocation decision is taken via the mean-variance formulation, which we will introduce next.

5.5.1 Mean-variance formulation of portfolio optimization

The mean-variance formulation proposed by Markowitz (1952) has been a classical model in financial portfolio optimization. The model receives its name from the combination of the two most important factors, *return* and *risk*, by the *mean* and *variance* of the return distribution of an investment portfolio. Markowitz and Todd (2000) further conclude that the mean-variance model provides the maximum expected utility for most most utility functions; see Wang and Xia (2002) for a detailed discussion. To construct a mean-variance model, however, we need information about the mean vector and variance-covariance matrix of the return distributions. The bootstrap methods developed in this chapter allow us to approximate efficiency distributions of R&D projects, from which we can derive the estimated mean and variance of a project portfolio.

We assume that the decision-maker has a quadratically concave utility function[8]. Consider an investor who receives n project proposals and has a fixed amount of resources to invest. The decision variables are the proportions of resources allotted to different projects, which is denoted by p_i, for $i = 1, \ldots, n$. We assume a budgetary rule under which the selected project has to be financed with at least 70% of its requested budget. The vector $\mathbf{p} = [p_1, \ldots, p_n]'$ is called a portfolio. The efficiency of project k is a random variable θ_k with mean $\mathbb{E}(\theta_k)$. Denote Σ to be the variance-covariance matrix of all project efficiencies and $\boldsymbol{\theta} = [\theta_1, \ldots, \theta_n]'$. It then follows that the mean and variance of the efficiency of a portfolio $\mathbf{p}$ is

$$\mathbb{E}(\mathbf{p}'\boldsymbol{\theta}) = \mathbf{p}'\mathbb{E}(\boldsymbol{\theta}) \text{ and } \operatorname{Var}(\mathbf{p}'\boldsymbol{\theta}) = \mathbf{p}'\Sigma\mathbf{p}, \text{ respectively.} \tag{5.11}$$

[8] This assumption is a sufficient condition to guarantee that the portfolio obtained from the mean-variance model is non-dominated; see Levy and Sarnat (1971).

Suppose the investor wants the portfolio to be mean maximizing and variance minimizing. Then the portfolio selection can be naturally formulated as a bi-criterion problem, which reflects the trade-off between risk and return[9]. In practice we often scalarize the problem to a mix-integer quadratic problem (5.12), which is NP-hard (Jobst et al 2001):

$$
\begin{aligned}
\max\ & \mathbf{p}'\mathbb{E}(\boldsymbol{\theta}) - \kappa(\mathbf{p}'\Sigma\mathbf{p}) && (5.12a)\\
\text{subject to}\ & \mathbf{p}'\mathbf{1}_n = \delta && (5.12b)\\
& y_i l_i \delta \leq p_i \leq y_i u_i \delta,\ i = 1, \ldots, n && (5.12c)\\
& y_i \in \{0, 1\},\ i = 1, \ldots, n. && (5.12d)
\end{aligned}
$$

The parameter $\kappa \geq 0$ specifies the investor's degree of aversion to risk: the higher the value, the more risk-averse the solution will be. Constraint (5.12b) states that the portfolio ratios should sum up to one; nonetheless this constraint can be relaxed. The δ represents the budget available for allocation. Constraints (5.12c) and (5.12d) express the 70% budget rule: so l_i is set to 70% and $u_i = 1$. The binary variables y_i represent the choice whether project i is selected.

Based on the same mean-variance concept, we can also formulate an alternative model by rearranging (5.12) and adding a portfolio efficiency constraint:

$$
\begin{aligned}
\min\ & \mathbf{p}'\Sigma\mathbf{p} && (5.13a)\\
\text{subject to}\ & \mathbf{p}'\mathbf{1}_n = \delta && (5.13b)\\
& \mathbf{p}'\mathbb{E}(\boldsymbol{\theta}) \geq \gamma && (5.13c)\\
& y_i l_i \delta \leq p_i \leq y_i u_i \delta,\ i = 1, \ldots, n && (5.13d)\\
& y_i \in \{0, 1\},\ i = 1, \ldots, n. && (5.13e)
\end{aligned}
$$

[9] The mean maximizing (given a upper bound for variance) and variance minimizing (given a lower bound for return) portfolios are called mean-variance efficient portfolios.

The parameter γ in (5.13c) represents the lowest mean efficiency that the investor can accept.

To obtain estimates of the mean vector and variance-covariance matrix of efficiencies, we apply the RCE, SW, and CE bootstrap algorithms to the project data shown in Tables 5.2. We illustrate the application via problem (5.12). The maximum budget for the R&D program is 1000 monetary units, and we set $\kappa = 0.7$ in problem (5.12). The problem can be efficiently solved to optimality using the branch-and-bound algorithm combined with the quadratic programming solver in most commercial softwares.

Table 5.1 lists the resource allocation results. In the table we also include with the allocation results according to efficiency evaluation and allocation approaches by Green et al (1996) and Liang et al (2008b). The efficiency scores obtained from these two approaches can be found in Table 5.3 in Appendix B. Their allocation decisions are taken simply by distributing the funding by the order of efficiency (from the highest to the lowest). After each step, if the remaining funding is insufficient to fully finance the next project, they will skip that project and continue going down the list, until either finding a project whose budget can be fully covered or reaching the end of the list. In terms of the l_i parameter in formulation (5.13), their approach implies that the budgeter is required to finance selected projects by 100%, or equivalently the task is only about project "selections". So if the 100% rule is indeed enforced, their allocation rule may seem straightforward and righteous. However, if the budgetary rule is relaxed (like in our case), the allocation method based on point estimates of efficiency scores will completely break down, regardless which efficiency model is used. On the contrary, our approach is applicable to both cases.

Table 5.1: R&D project budgeting: a comparison

Project	Green et al	Liang et al	SW's alg.	Alg. 2	Alg. 5
1	84.2	84.2	0.0	58.9(70%)	0.0
2	0.0	0.0	0.0	0.0	0.0
3	0.0	0.0	0.0	0.0	0.0
4	0.0	0.0	67.5(100%)	0.0	0.0
5	0.0	0.0	0.0	0.0	0.0
6	0.0	0.0	0.0	0.0	0.0
7	0.0	0.0	0.0	0.0	0.0
8	0.0	0.0	0.0	0.0	0.0
9	0.0	0.0	0.0	0.0	0.0
10	0.0	0.0	0.0	0.0	54.3(70%)
11	0.0	0.0	0.0	53.6(70%)	53.6(70%)
12	47.5	47.5	47.5(100%)	47.5(100%)	47.5(100%)
13	0.0	0.0	58.5(100%)	58.5(100%)	58.1(99%)
14	95.0	95.0	0.0	0.0	0.0
15	0.0	83.8	83.3(98%)	0.0	0.0
16	35.4	35.4	35.4(100%)	35.4(100%)	35.4(100%)
17	32.1	32.1	32.1(100%)	32.1(100%)	32.1(100%)
18	46.7	46.7	46.7(100%)	46.7(100%)	46.7(100%)
19	0.0	0.0	0.0	0.0	0.0
20	0.0	0.0	0.0	0.0	0.0
21	74.4	74.4	74.4(100%)	52.1(70%)	52.1(70%)
22	0.0	0.0	0.0	0.0	0.0
23	75.6	75.6	75.6(100%)	75.6(100%)	75.6(100%)
24	0.0	0.0	0.0	0.0	0.0
25	0.0	0.0	0.0	0.0	0.0
26	69.3	69.3	69.3(100%)	69.3(100%)	69.3(100%)

-Continued on next page-

Project	Green et al	Liang et al	SW's Alg.	Alg. 2	Alg. 5
27	57.1	57.1	57.1(100%)	57.1(100%)	57.1(100%)
28	0.0	0.0	0.0	0.0	0.0
29	72.0	0.0	59.0(82%)	72.0(100%)	72.0(100%)
30	0.0	0.0	0.0	0.0	0.0
31	44.6	44.6	44.6(100%)	44.6(100%)	44.6(100%)
32	54.5	54.5	54.5(100%)	54.5(100%)	54.5(100%)
33	0.0	0.0	0.0	47.6(90%)	52.7(100%)
34	28.0	28.0	28.0(100%)	28.0(100%)	28.0(100%)
35	36.0	36.0	36.0(100%)	36.0(100%)	36.0(100%)
36	64.1	64.1	64.1(100%)	64.1(100%)	64.1(100%)
37	66.4	66.4	66.4(100%)	66.4(100%)	66.4(100%)
Total:	982.9	994.7	1000	1000	1000

In Table 5.1, the last three columns are the allocation decisions according to the mean-variance model in combination with different bootstrap algorithms. The allocation results involve the amount and the percentage of budget allocated permitted. By comparing the results from the two categories of approaches (columns 2 and 3 v.s. columns 4, 5 and 6), we can discover the advantages of our methodology. First, although Green et al (1996) and Liang et al (2008b) have used alternative DEA method to derive the Cross-Efficiency scores[10], their methods basically select projects based on the ordinal ranking of the efficiency scores, and therefore they are unable to incorporate risk-mitigating effect into the selection process. Note that selecting projects without considering the inter-project relations will result in dominated project portfolios (Graves and Ringuest, 2003). Second, as noted, these approaches can only make binary selections and do not consider the

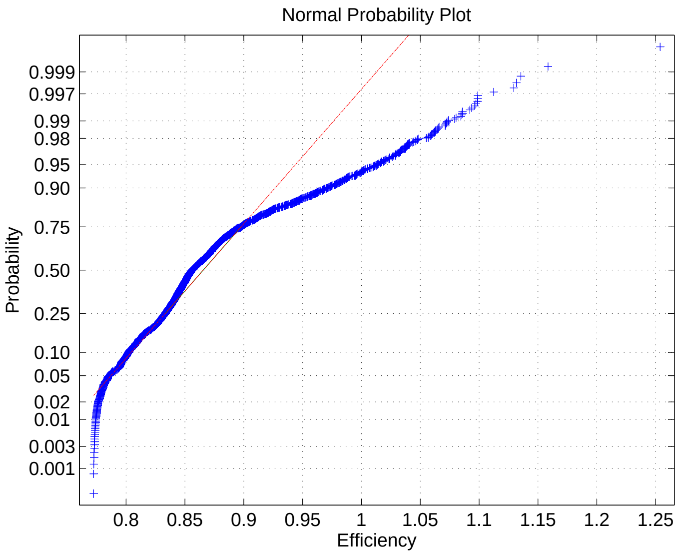
[10] See Appendix A for an introduction to the cross-efficiency DEA method.

integrated portfolio performance. Our approach can allocate budgets to optimize the mean-variance performance of project portfolios.

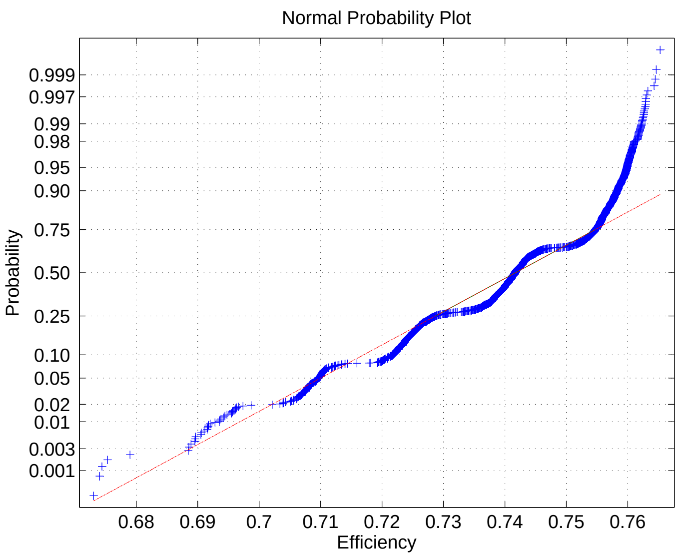
5.6 Application 2: Normalization procedures for bootstrap distributions

In this chapter we have touched upon three bootstrap algorithms: SW, RCE, and CE. No matter which algorithm we choose, we need to elicit information from the bootstrap distributions. Many statistical procedures assume (multivariate) normality of the population; for example, ANOVA, discriminant analysis (see, e.g., Sharma, 1995), and many Ranking & Selection (R&S) methods and multiple comparisons methods (see, e.g., Kim and Nelson, 2006). The bootstrap distributions of efficiencies, however, are not guaranteed to be normally distributed—this is true for SW's method, the RCE method, and the cross-efficiency approach detailed in Appendix A. For instance, Figure 5.3 is the normality plot of the bootstrap distributions using SW's and the RCE algorithms. Simply by visual inspections we already can see that these two distributions deviate quite substantially from normal distributions. More precisely, using the Shapiro-Wilk normality test under a 5% significance level shows that both distributions deviate significantly from the hypothesized normal distributions ($p < 1\%$). The non-normality can be problematic when we intend to apply methods that require normality of the bootstrap outputs.

In this final application, we introduce a normalization procedure to preprocess the bootstrap data. In particular, we propose an algorithm based on the non-overlap batch means method to convert the distribution of simulation outputs to distributions of sample mean efficiencies. Formally, given a batch size k and a sequence of m stochastic processes $\Theta_1, \Theta_2, \ldots, \Theta_m$ with $E(\Theta_i) = \theta$. If $m/k = n$ is an integer, we can divide the stochastic processes into n batches $\Theta(1)$ to $\Theta(n)$. The batch means are then defined by



(a) SW's alg.



(b) Alg. 2

Fig. 5.3. Bootstrap efficiency distributions of project#37 ($B = 500$)

$$\bar{\Theta}(i) = (\mathbf{1}_k' \Theta(i))/k, \text{ for } i = 1 \text{ to } n. \tag{5.14}$$

If k is large enough, it can be shown that $\mathbb{E}(\bar{\Theta}(i)) = \theta$ and the $\bar{\Theta}(i)$'s are uncorrelated (Law, 2007). We should note that the batch means method is mostly used to mitigate the influence of the *startup problem* in steady-state simulation experiments, for example, of queueing systems (Law, 2007). Kim and Nelson (2007) suggest using the batch means method to convert non-normal simulation outputs when normality is required.

In our case, we are concerned with the normality condition of bootstrap distributions, rather than the dependence problem in most steady-state simulation experiments, since we use Monte Carlo simulation in the algorithms. Yet we still need to determine the batch size k, give a fixed number of bootstrap replications B. By the Central Limit Theorem, we know that, as k increases to infinity, the batch means will be normally distributed. However, since we have a fixed number of B observations, specifying k too large will delete the samples of batched means. We can avoid this problem by searching for the minimal k that renders all batch means distributions normally distributed. For univariate normality test, we apply the Shapiro-Wilk test (Shapiro and Wilk, 1965). Numerous tests exist for testing multivariate normality; for example, Royston's Multivariate Normality Test (Royston, 1983); see Mecklin and Mundfrom (2005) for a comparison of different testing procedures.

In determining the normality of distributions, we need to perform multiple statistical tests. Consequently, it requires an appropriate procedure to guard against the rising Type-I error probability due to multiple tests. One simple method is to make use of the Bonferroni inequality. Formally, let $E_1, E_2, \ldots, E_n$ denote n events in the sample space, the Bonferroni inequality gives the following relationship:

$$P_r(\bigcap_{i=1}^{n} E_i^c) \leq \sum_{i=1}^{n} P_r(E_i^c). \tag{5.15}$$

Therefore (5.15) assures that if we conduct n comparisons at the significance level α/n, the overall Type-I error rate will be less than or equal to α. The Bonferroni method has several merits: it is easy to implement, and it can be applied regardless of the data structure. Unfortunately, a serious limitation of the method is its tendency to be overly conservative (i.e., the nominal overall significance level is much higher than the real value), and as a result the probability of Type II errors increases. We can also see that the problem will become serious as n grows larger. Other improved methods based on the Bonferroni's inequality also exist (see, e.g., Troendle, 1995).

In Bonferroni's procedure, the overall significance level is divided by n because we can potentially make Type-I errors for n times. A simple way to improve is to account for the number of rejections in previous tests. So, for example, when k hypotheses have been rejected, the significance level in the next test can be set to $\alpha/(n-k)$, while the overall Type-I error rate are still bounded above by α. Hochberg's procedure is an extension of the idea Hochberg (1988). We can easily prove that the procedure is uniformly more powerful than Bonferroni's. In Hochberg's procedure, we consider n null hypotheses $H_1, H_2, \ldots, H_n$ to be jointly tested. For hypothesis i, we can compute test statistics t_i and the associated p-value p_i, for $i = 1, \ldots, n$. Given an overall significance level α, Hochberg's procedure proceeds as:

Algorithm 3 Hochberg's procedure

1: sort p_i for $i = 1, \ldots, n$ to be $p_{[1]} \geq p_{[2]} \geq \ldots \geq p_{[n]}$. Set $i = 1$.
2: **if** $p_{[i]} \leq \alpha/i$ **then**
3:    reject hypotheses from H_i to H_n and STOP.
4: **else**
5:    accept H_i, increase i by one, and go to STEP 2.
6: **end if**

Note that Hochberg's algorithm is constructed for a "static" situation. This means that the sample sizes are predetermined and therefore the p-values are available beforehand. For the purpose of batch means, we need to adapt Hochberg's algorithm to accommodate the changing sample sizes.

Next we will propose an algorithm to deal with the issue of multiple hypothesis testings by progressively increasing k. The steps are stated as follows:

Algorithm 4 The batch means procedure

1: set the batch size $k = 1$, and the batch means sample size $n' = \lfloor n/k \rfloor$, and the nominal overall significance level α.
2: **for** $i = 1$ to n **do**
3: generate distributions of batch means θ_i based on k and n', for $i = 1$ to n.
4: calculate the Shapiro-Wilk test statistics W_i and the associated p-value p_i of bootstrap distribution for $i = 1, \ldots n$.
5: **end for**
6: call Algorithm 3.
7: **if** all hypotheses are maintained (i.e., $p_{[n]} \leq \alpha/n$) **then**
8: STOP.
9: **else**
10: increase the batch size by one, and return to STEP 2.
11: **end if**

We apply Alg. 4 to the bootstrap distributions shown in Figure 5.3. The algorithm terminates at the batch sizes of 5 and 6 for two distributions (with the replication size $B = 500$), respectively. We can also see from Figure 5.4 that the batch means distributions are distributed closer to the hypothesized normal distributions, as compared to the original bootstrap distributions shown in Figure 5.3.

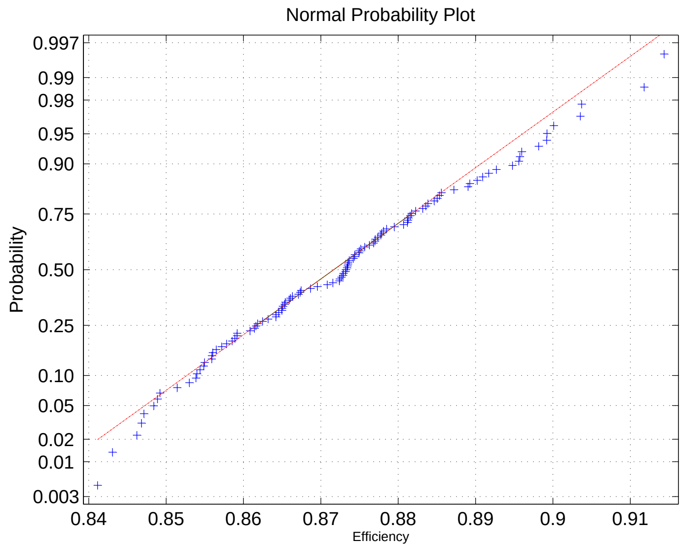
A problem of Alg. 4 is that we cannot guarantee that B is large enough to achieve the normality condition, as the required batch size also depends on how "non-normal" the bootstrap distributions are. In other words, we cannot determine the value of B a priori. This issue, of course, can be solved by inserting an interactive procedure in Alg. 4, such that when the batch size increases to a certain extent we will need to do more bootstrap replications. In our case, though, setting $B = 500$ is sufficient for the procedure to stop before the batch size overflows the number of bootstrap replications (i.e., the sample sizes fall below 3). However, if we can increase B when necessary, the algorithm will always terminate in finite time by the Central Limit Theorem and the principle of bootstrapping.

Lemma 5.1. *Alg. 4 will terminate in finite time given that* B *tends to infinity.*

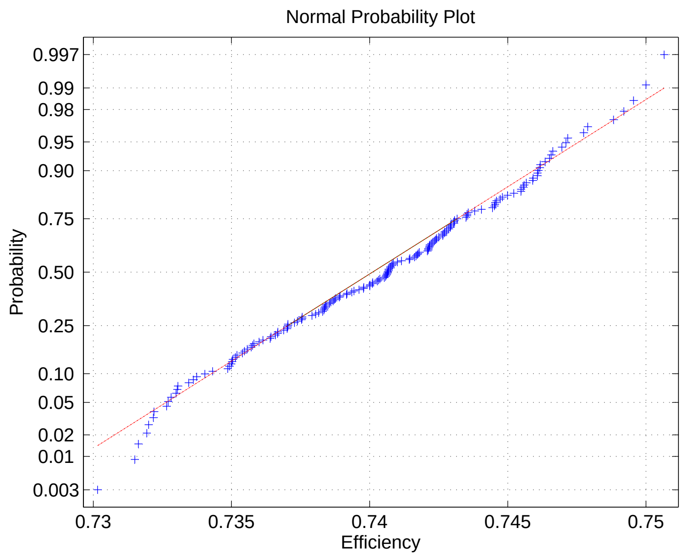
5.7 Conclusions

In this chapter we have developed novel approaches to policy selection decisions under uncertainty. This chapter contributes to the literature in several ways. For the process design literature, this study proposes a multi-factor evaluation model for the selection of policies and the corresponding resource allocation problems. We have tackled the resource allocation problem in the one-sample situation, which is common in today's fast changing market. In the application section, we apply the proposed methodology to the resources allocation problems in the context of R&D project selection.

The current study also contributes to the literature on efficiency evaluation by developing bootstrap algorithms associated with the revised DEA multiplier model. Relative to the traditional DEA and the cross-efficiency methods, the revised multiplier model has the advantage of stability in estimation, while it retains the merit of the cross-efficiency method of being discriminating in evaluation. The revised model also rectify the sensitivity results that can arise in the DEA bootstrap outputs. One promising follow-up direction is to further investigate the relationship between revised model and the cross-efficiency methods, since both methods share a similar concept of efficiency. In this study we also present a normalization procedure that renders bootstrap outputs amenable to various statistical methods that require a normality assumption. As an illustration, the procedure is applied to the bootstrap outputs of the project selection



(a) Batch means ($k = 18$) of the bootstrap distribution generated by SW's alg.



(b) Batch means ($k = 12$) of the bootstrap distribution generated by Alg. 2

Fig. 5.4. The batch means distribution of the efficiency of project-37 ($B = 500$)

problem. The result shows that our normalization procedure is effective and efficient in transforming the bootstrap distributions into normal ones.

Appendix A: the DEA cross-efficiency model and its bootstrap algorithm

Recall that in the DEA multiplier model (5.5) the input and outputs weights of a DMU is determined such that the DMU's efficiency is optimized, given the typical $[0, 1]$ bound on the efficiency value. This means that each unit has the freedom to select its preferred weights, yet the weights selected present no impact no the evaluation of other units. The independence of weight selections may seem awkward for problems in which each unit's "opinion" counts to a certain degree, such as the preference voting example considered in Green et al (1996), and the project selection example used in this chapter. The DEA cross-efficiency (CE) method is a commonly used approach to the above problem.

The CE score is constructed based on optimal solutions to the DEA multiplier model (5.5). Recall that after the DEA evaluation, we can obtain n sets of weights corresponding to n DMUs. Now denote the optimal solution to (5.5) for DMU k by the pair $(\hat{\boldsymbol{\nu}}_k, \hat{\boldsymbol{\mu}}_k)$, where $\hat{\boldsymbol{\nu}}_k = [\hat{\nu}_{k1}, \dots, \hat{\nu}_{ki}]$ and $\hat{\boldsymbol{\mu}}_k = [\hat{\mu}_{k1}, \dots, \hat{\mu}_{kj}]$. The CE score for DMU k is defined as:

$$\mathrm{CE}_k = n^{-1} \sum_{r=1}^{n} \frac{\sum_{q=1}^{j} \hat{\mu}_{rq} Y_{kq}}{\sum_{p=1}^{i} \hat{\nu}_{rp} X_{kp}}. \tag{5.16}$$

The CE is the average of efficiency scores associated with optimal weights determined by individual DMUs. So a unit's CE score is derived after considering weights "across" its and other units' weight vectors. In application, the CE has two main features. First, DEA evaluation results often have multiple efficient DMUs. In this regard, the CE method can be used to further distinguish efficient DMUs and increase the discrimination power in the result (Adler et al, 2002), because by construction CE scores of all DMUs are almost always discrepant. Second, the CE method is considered as a democratic evaluation process, as compared to traditional DEA models, since DEA models determine the efficiency score according to the perspective of the evaluated DMU only Doyle and Green (1994). Therefore, the CE method has been extensively applied in many evaluation problems; see, among others, Oral et al (1991); Doyle and Green (1994); Shang and Sueyoshi (1995); Green et al (1996); Chen (2002); Talluri and Narasimhan (2004); Liang et al (2008b).

Determination of unique optimal weights

As mentioned, the CE score depends on the optimal weights from the DEA solutions. Problem (5.5), however, is often degenerate and thus non-unique; the exact solution will depend on the optimization packages used (Despotis, 2002). Several studies in the literature has provided antidotes to the problem. Doyle and Green (1994) propose an auxiliary procedure to determine a set of unique weights, given the evaluated DMU's DEA efficiency score. Specifically, Doyle and Green solve the following optimization problem:

$$\min \sum_{q=1}^{j}\sum_{k=2}^{n} \mu_{1q} Y_{kq} \Big/ \sum_{p=1}^{i}\sum_{k=2}^{n} \nu_{1q} X_{kq} \tag{5.17a}$$

$$\text{subject to } \sum_{q=1}^{j} \mu_{1q} Y_{1q} \Big/ \sum_{p=1}^{i} \nu_{1q} X_{1q} - \theta_1 = 0, \tag{5.17b}$$

$$\sum_{q=1}^{j} \mu_{1q} Y_{kq} - \sum_{p=1}^{i} \nu_{1p} X_{kp} \leq 0, \; k = 1, \ldots, n, \tag{5.17c}$$

$$\mu_{1q}, \nu_{1p} \geq 0, \; p = 1, \ldots, i, \; q = 1, \ldots, j. \tag{5.17d}$$

In problem (5.17), the objective function is the weighted output-input ratio of the other DMUs except DMU 1 (the evaluated DMU); constraint (5.17a) ensures that the weights are optimal to problem (5.5), and constraint (5.17b) is used to maintain the efficiency score θ_1 obtained from (5.5). So problem (5.17) searches, among the optimal solutions to (5.5), the set of weights that minimizes the weighted output-input ratio of all the other DMUs. Problem (5.17) is thus called the *aggressive* formulation due to its objective function. Sexton et al (1986) develop a similar method, called the *benevolent* formulation, that instead maximizes the same objective as in (5.17a). See also Liang et al (2008a) and Liang et al (2008b) for other methods to derive the weights for CE scores.

Next we introduce the bootstrap algorithm for the CE model. Like the DEA bootstrapping algorithm, the CE bootstrap algorithm can generate approximated distributions of CE scores, which can be used for inferences and comparisons on the CE scores of sampled DMUs. To develop the algorithm, we start by constructing the probabilistic model of the CE method.

Probability model and bootstrap algorithm

For all DMUs, the feasible region of problem (5.4) is a polyhedron associated with the sample size n, which also implies that the DEA results will depend on our estimate of the polyhedron. For now, we assume that the sequence of polyhedra converges downwards to a nonempty region of permissible weights, as the sample size tends to infinity:

$$(\boldsymbol{\nu}, \boldsymbol{\mu}) := \bigcap_{k=1}^{\infty} \left\{ (\nu_{kp}, \mu_{kq}) : \sum_{q=1}^{j} \mu_{kq} Y_{kq} - \sum_{p=1}^{i} \nu_{kp} X_{kp} \leq 0 \right\} \subset \Re_{+}^{i \times j}. \tag{5.18}$$

By (5.4b), the estimate of (5.18) based on a sample of size n can be represented by

$$(\hat{\boldsymbol{\nu}}_{\boldsymbol{n}}, \hat{\boldsymbol{\mu}}_n) = \bigcap_{k=1}^{n} \left\{ (\nu_{kp}, \mu_{kq}) : \sum_{q=1}^{j} \mu_{kq} Y_{kq} - \sum_{p=1}^{i} \nu_{kp} X_{kp} \leq 0 \right\}. \tag{5.19}$$

We then arrive at the following convergence result:

Theorem 5.2. *The set sequence defined in* (5.19) *is non-increasing and will converge in probability to* (5.18)*; i.e.,*

$$(\hat{\boldsymbol{\nu}}_{\boldsymbol{n}}, \hat{\boldsymbol{\mu}}_n) \xrightarrow{P} (\boldsymbol{\nu}, \boldsymbol{\mu}).$$

The above proposition can be deduced from the the radial DEA formulation according to duality properties; see Banker (1993), Korostelev et al (1995), Kneip et al (1998) and Simar and Wilson (2000) for the primal construction of the efficiency estimation problem[11]. Therefore, we can regard (5.19) as a finite sample approximation of the *true* polyhedron $(\boldsymbol{\nu}, \boldsymbol{\mu})$ in (5.18). Recall that after solving (5.5) for each DMU, we obtain a set of optimal input-output weight vectors $(\hat{\mu}_{kq}, \hat{\nu}_{kp})$, $k = 1, \ldots, n$, by which we can calculate the CE scores. Following the notations introduced earlier, we construct the empirical distribution of DMUs (F_1) by putting probability mass $1/n$ on each DMU[12]. We can now generate bootstrap samples by drawing samples from F_1:

$$F_1 \rightarrow \big((X_1, Y_1)^*, \ldots, (X_n, Y_n)^*\big), \tag{5.20}$$

from which we can obtain bootstrap replications by computing $\widehat{CE}_k^*$ as in (5.16), for $k = 1, \ldots, n$. By repeatedly sampling from F_1, we can approximate the distributions of CE scores. The process of deriving $\widehat{CE}_k^*$ is referred to as the multiparameter problem in the literature; see, e.g., Efron and Tibshirani (1986) and Efron (1987) for further discussions. Note that the equivalence of problem (5.4) and problem (5.5) implies that weight estimates obtained from (5.5) must be optimal for (5.4) as well.

We summarize the above bootstrap procedure in Algorithm 5:

[11] There are few assumptions necessary for the convergence results in the primal efficiency framework: (1) i.i.d. sampling, (2) a convex production set, (3) efficient units will be observed with probability one as $n \to \infty$. See Banker (1993).

[12] This approach is analogous to bootstrapping pairs in the regression analysis; see, e.g., Chap. 9 of Efron and Tibshirani (1993).

Algorithm 5 CE bootstrap algorithm

1: **for** $b = 1$ to B **do**
2: sample with replacement from the empirical input-output pairs to generate bootstrap samples $(X_{kb}, Y_{kb})^*$, $k = 1$ to n.
3: **if** the bootstrap sample is degenerate (all input-output pairs in the resample are identical) **then**
4: set $\hat{w}^*_{kb} = (\hat{\nu}^*_{kb}, \hat{\mu}^*_{kb})$, where $\hat{\nu}^*_{kbp} = 1\Big/\sum_{p=1}^{i} X_{1p}$, $\hat{\mu}^*_{kbq} = 1\Big/\sum_{q=1}^{j} Y_{1q}$, $\forall k, p, q$.
5: **else**
6: estimate the input-output weight vector $\hat{w}^*_{kb}$ by using models (5.5) and (5.17), for $k = 1$ to n.
7: compute $\widehat{CE}^*_{kb}$ according to (5.16), for $k = 1$ to n.
8: **end if**
9: **end for**
10: obtain the bootstrap distribution of $\widehat{CE}^*_{k}$, for $k = 1$ to n.

In STEP 2, we resample the observed input/output units to estimate the weight vector in STEP 6. STEPs 3 and 4 are developed to avoid the degenerate case, where the resample consist of only replicas of one specific empirical sample and thus we would be unable to determine the optimal weight vector uniquely. Hence in the algorithm we regulate that, if the bootstrap sample is degenerate, then the weights are specified as shown in STEP 4, in which input and output variables are assigned equal weights. The probability of obtaining a degenerate resample, however, is fairly insignificant in practice. On the other hand, if the resample is non-degenerate, we can proceed to compute the bootstrap weights by invoking models (5.5) and (5.17) for the resample. Provided the bootstrap weights, the bootstrap distributions of CE are straightforward (STEPs 7 and 10).

Finally, the model of efficiency estimation introduced in this section is based on the DEA multiplier model (5.4). Recall that the DEA multiplier and radial formulations have a primal-dual relationship. Based on this relationship, we can look at the statistical property that DEA provides an underestimate of inefficiency (or equivalently, an overestimate of efficiency) from two different perspectives. As noted in earlier chapters, the DEA radial model provides a downward biased estimate of the true production frontier under the concavity and monotone assumptions; i.e., the estimated estimated production feasible set is a subset of the true one. Thus the radial DEA model tends to overestimate the efficiencies. In contrast, the estimated feasible region of weights (5.19) is an overestimate of (5.18) in the multiplier model. Hence the actual freedom of weight selection should be smaller, which means that the efficiency will tend to be overestimated, just like in the radial model. More specifically, model (5.4) tends to get *tighter* bounds on weights when the sample size increases—for (5.5c), once a larger sample is involved, more constraints will then be introduced in the problem. This can be contrasted with the radial DEA model, in which the production feasibility set cannot be reduced by the addition of new observations.

Appendix B: example data and results from previous approaches

Table 5.2: R&D project proposal data set

Project	[1]	[2]	[3]	[4]	[5]	Budget
1	67.53	70.82	62.64	44.91	46.28	84.20
2	58.94	62.86	57.47	42.84	45.64	90.00
3	22.27	9.68	6.73	10.99	5.92	50.20
4	47.32	47.05	21.75	20.82	19.64	67.50
5	48.96	48.48	34.90	32.73	26.21	75.40
6	58.88	77.16	35.42	29.11	26.08	90.00
7	50.10	58.20	36.12	32.46	18.90	87.40
8	47.46	49.54	46.89	24.54	36.35	88.80
9	55.26	61.09	38.93	47.71	29.47	95.90
10	52.40	55.09	53.45	19.52	46.57	77.50
11	55.13	55.54	55.13	23.36	46.31	76.50
12	32.09	64.04	33.57	40.60	29.36	47.50
13	27.49	39.00	34.51	21.25	25.74	58.50
14	77.17	83.35	60.01	41.37	51.91	95.00
15	72.00	68.32	25.84	36.64	25.84	83.80
16	39.74	34.54	38.01	15.79	33.06	35.40
17	38.50	28.65	51.18	59.59	48.82	32.10
18	41.23	47.18	41.01	10.18	38.86	46.70
19	53.02	51.34	42.48	17.42	46.30	78.60
20	19.91	18.98	25.49	8.66	27.04	54.10
21	50.96	53.56	55.47	30.23	50.44	82.10
22	53.36	46.47	49.72	36.53	50.44	82.10
23	61.60	66.59	64.54	39.10	51.12	75.60
24	52.56	55.11	57.58	39.69	56.49	92.30

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Project	[1]	[2]	[3]	[4]	[5]	Budget
25	31.22	29.84	33.08	13.27	36.75	68.50
26	54.64	58.05	60.03	31.16	46.71	69.30
27	50.40	53.58	53.06	26.68	48.85	57.10
28	30.76	32.45	36.63	25.45	34.79	80.00
29	48.97	54.97	51.52	23.02	45.75	72.00
30	59.68	63.78	54.80	15.94	44.04	82.90
31	48.28	55.58	53.30	7.61	36.74	44.60
32	39.78	51.69	35.10	5.30	29.57	54.50
33	24.93	29.72	28.72	8.38	23.45	52.70
34	22.32	33.12	18.94	4.03	9.58	28.00
35	48.83	53.41	40.82	10.45	33.72	36.00
36	61.45	70.22	58.26	19.53	49.33	64.10
37	57.78	72.10	43.83	16.14	31.32	66.40

[1]: Indirect economic contribution
[2]: Direct economic contribution
[3]: Social contribution
[4]: Technical contribution
[5]: Scientific contribution

* Source: Oral et al (1991).

Table 5.3: Efficiency scores and rankings from Green et al (1996)'s and Liang et al (2008b)'s models

Project	Liang et al (2008b)	Green et al (1996)
1	0.633	0.614
2	0.534	0.591
3	0.239	0.259
4	0.468	0.457
5	0.479	0.457
6	0.561	0.528
7	0.464	0.436
8	0.417	0.409
9	0.474	0.444
10	0.535	0.525
11	0.554	0.544
12	0.542	0.530
13	0.490	0.466
14	0.629	0.611
15	0.583	0.537
16	0.816	0.780
17	0.999	0.975
18	0.737	0.715
19	0.502	0.484
20	0.329	0.307
21	0.584	0.565
22	0.490	0.472
23	0.670	0.655
24	0.491	0.476
25	0.380	0.359

-Continued on next page-

Project	Liang et al (2008b)	Green et al (1996)
26	0.650	0.632
27	0.729	0.712
28	0.341	0.331
29	0.571	0.559
30	0.545	0.538
31	0.908	0.866
32	0.621	0.606
33	0.419	0.404
34	0.737	0.699
35	1.000	1.000
36	0.767	0.759
37	0.705	0.684

Part III

Conclusions and future directions

6

Conclusions and future directions

Supply chain management (SCM) has become one of the most important strategies to enhance business performance and competitiveness. Successful SCM, however, requires more than smart tactics or optimized physical flows of products/services; it also relies much on the joint integration of various processes across organizational borders. Integration and coordination of supply chain operations certainly cannot be accomplished overnight. This requires careful long-term planning, design, execution, and, above all, appropriate performance measures to oversee the entire process and to make necessary adjustments. Under intensified pressure from customers and competitors, managers nowadays need to frequently make proactive policy decisions and advanced planning, which usually have direct and substantial influences on the firm's future performance. To achieve long-term combativeness, we need to focus on design, evaluation, and subsequent improvements of the supply chain operations.

Through a critical review of the literature, this thesis has identified important characteristics of supply chain performance and the challenges to evaluate and design supply chain processes. In particular, we identify "multiple inputs and outputs of different firms at different times", "dynamic interactions among firms in the network", and "coordination of performance measurement and improvement actions among different levels of processes in a supply network", as the three main characteristics. For the design problems, we find that the major issue lies in the uncertainty of the system's future performance concerning multiple inputs and outputs. Based on the Data Envelopment Analysis (DEA) approach, this thesis proposes new methodologies to tackle these issues.

To precisely capture the performance of a supply chain, we model the dynamic interrelations among the production process of firms. Our approach can evaluate both individual firms and the production network in a systematic way. The evaluation results concerning entities at different levels can effectively assist managers to identify critical points for subsequent improvements. This thesis develops integrated methodologies to evaluate and design complex production processes. Our evaluation approach is developed mainly based on DEA (Data Envelopment Analysis) model to consider multiple inputs and multiple outputs in system evaluation. DEA has been widely applied as a tool to assess the multi-factor performance of organizations in a variety of contexts. Classical DEA models, however, assume that the temporal production is independent over time, and therefore are unable to deal with dynamics in production (i.e, when current production inputs can influence future outputs). In Chapter 2, we generalize the widely used static DEA model by incorporating dynamic elements into the model, and utilize econometric models to estimate the dynamic intensity; this chapter also introduces several interesting theoretical properties of the dynamic model. The empirical result in this chapter shows that using traditional efficiency measures in dynamic production can lead to biases in efficiency measuring, either in terms of efficiency scores or rankings.

Chapter 3 makes use of the principle of the dynamic DEA model developed in Chapter 2, and extend the dynamic model to a network production setting. To adapt the conventional performance measures to the network environment, we develop an approach to measure both the performance of production networks and their constituting production units. Therefore, managers at different levels can benefit from information in the measuring results; subsequently they can improve local performance in a way consistent with the supply network performance. We also show the necessary and sufficient conditions to achieve efficiency status in the dynamic and production network. In addition, we investigate the returns-to-scale properties in the network context, and find that the returns-to-scale of the production network rely on those of the firms in the network.

In the second part of the dissertation, we develop methodologies that combine DEA and simulation-based techniques to support decision-making in supply chain planning. In particular, we develop two evaluative frameworks with respect to two classes of decision problems, namely *risky* and *uncertain* decision problems with multiple performance dimensions. For the first class of problems, Chapter 4 integrates subset selection, DEA and multiple comparisons to create a flexible yet efficient procedure to rank policy alternatives. This chapter also provides an application of this method, in which warehouse managers want to select a combination of order picking policies in three warehouses under varying demand scenarios.

The *uncertain* problems assume that only one observation (or estimation) of the production inputs and outputs is available. In Chapter 5, we propose two bootstrap algorithms for cross-efficiency scores to assess the variation in efficiencies. The algorithms are applied to project budgeting problems via the mean-variance portfolio model—we can strike the optimal trade-offs between efficiency variations and mean efficiencies in resource allocation. In the last application, we employ a batch means method to normalize the bootstrap efficiency distributions. This normalization procedure (i.e., batch means) is necessary before we can employ various statistical techniques, such as ranking and selection methods and multivariate statistical methods, to analyze the bootstrap efficiency distributions.

6.1 Findings and contributions

The contributions and findings from this thesis can be briefly summarized as follows:

- We develop the dynamic DEA model to evaluate the dynamic efficiency of firms. In this model, firms' production processes in different time periods are dynamically interrelated. The empirical application shows that using conventional DEA models could lead to significantly biased evaluation results in dynamic production situations.
- Following the concepts of dynamic DEA models, we propose an evaluation approach for production networks. The approach can provide specific evaluation results to firms according to their positions in the production network. We also show that breaking down the production processes of supply networks for evaluation can generate more practical insights in how to improve the supply network performance, either in terms of technical or scale efficiencies.
- Instead of evaluating the past, in process design problems we need to analyze future performance of the business process. We integrate DEA with simulation and statistical techniques to tackle process design problems under two different informational assumptions. Using our approaches, managers can optimize their decision-making with only incomplete information about the future environment.

Through this thesis we have identified the main issues in the evaluation and design of complex production processes, and developed corresponding approaches to deal with these issues. This thesis has contributed to the literature on both the theory and applications of supply chain evaluation and planning. In face of the growing importance and evolving development of SCM, the approaches in this thesis can be used to monitor, improve, and sustain the optimal efficiency performance of supply chains.

The proposed methodologies also form a strong foundation for future work, which will be elaborated in the next section.

6.2 Directions for future works

One extension to our dynamic DEA model developed in Chapter 2 is to relax the output disposability assumption in dynamic production processes. The disposability property adopted in our model implies that lagged effects always have a nonnegative impact on the subsequent production. However, in some situations, lagged effects can negatively influence the production. For instance, agriculturists use fertilizer and pesticides to increase production over limited cultivated lands. These artifacts, however, can also pollute surface and underground waters, "*...incurring health and water purification costs, and decreasing fishery and recreational values.*"(Tilman et al 2002). The impact of hazardous substances on the environment and users may have a window period before it becomes observable.

In our dynamic model, we specify lag parameters to be constant for all firms at all times. However, lagged effects may depend on firm sizes, and lagged effects may be time-varying as well (e.g., Henderson and Cockburn, 1996). Relaxing these assumptions on lagged effects can be a promising direction for future research. The dynamic DEA models developed in Chapter 2 can be applied to a wide range of practical situations, including evaluating the effect of investments in IT systems and environmental improvements, human resources and the pollution effect, as mentioned in Chapter 2. There is a vast body of studies in different disciplines, all concerning evaluating longitudinal performance and efficiency changes of firms (e.g., Färe et al, 1994; Thursby and Thursby, 2002; Banker et al, 2005). The dynamic DEA model can benefit these studies by providing a more accurate estimation of firms' performance over time.

In Chapter 3 the dynamic parameters in the network DEA model are assumed to be known. Thus one follow-up direction is to incorporate econometric methodologies (e.g., the PVAR model used in Chapter 2), stochastic modeling techniques or resort to expert opinion to appropriately determine the empirical values of the dynamic parameters. In Chapter 4 we embed DEA in the simulation framework; this brings up a theoretical issue worth further investigation. Several studies in the literature have used simulation to investigate the statistical properties of DEA as an estimator of efficiency. The statistical aspects of the distribution of an evaluated unit across multiple observations, however, have not received further attention. Establishing the statistical fundamentals of efficiency distributions of individual decision making units can be an important breakthrough, and further generalizes the framework.

In part II we deal with the design problem of a single process; e.g., selecting suppliers or R&D projects. In practice, in the course of constructing a large-scale supply network, managers should design production processes "for the better good of the supply network." In particular, specifications of the network should be determined according to the supply network view to achieve maximized performance and resolve conflicts among chain participants. Therefore in future work we can adopt the dynamic network DEA model in the design approaches developed in Part II.

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Summary in Chinese

供應鏈管理已成為現今企業增加其績效與競爭力的重要策略。然而，供應鏈管理所需的不只是各項生產、物流作業的短期改善；更重要的，它還包括了諸多跨企業流程的整體整合—如相關的各項長期規劃、流程設計、執行，和適當的績效評量方法，以提供供應鏈夥伴監控、調整與改善供應鏈專案之機制。此外，在市場競爭與顧客要求逐漸提高之際，今日之企業管理者必須頻繁的對企業中各項流程提出先見的規劃或調整，而這些決定常會對企業的績效有著眾大的影響。總上所述，企業流程之設計、評估與改善之各項問題，已儼然成為今日企業在供應鏈中成功的首要課題。

在本論文中，我們提出了各項整合式的企業流程評估與設計方法。本文中的方法是利用資料包絡分析(DEA)法，以期考慮生產中的各項投入與產出變數。為了精確量測供應鏈的績效表現，本方法考量了在供應鏈中各項企業流程的動態相互關係；此外，本方法可用於評估供應鏈整體、以及其組成企業的經營績效—故本方法產生的評量結果，可提供供應鏈中不同位階之管理者改善其生產效率之參考。本論文的第二部分，針對兩類不同的資訊條件下，提出了不同的流程設計方式。此方式結合了流程評估與模擬方法，以評估各式設計方案以及資源配置。為了提高在實際應用上的彈性，本方式同時還允許決策者參與設計過程。本文最後

提供了本方式於倉儲撿貨系統，以及企業研發專案選擇問題上的應用。

最後，茲整理本論文中各章之貢獻要點如下：

- 本文提出了動態的 DEA 方法，以評量企業持續經營的動態績。在此方法中，在不同時間中之企業生產流程存在著相互關係。我們的實證結果顯示，在此種動態經營環境下，傳統之 DEA 方法會產生顯著錯誤與偏差的評量資訊。
- 根據上述動態 DEA 方法之概念，本文進一步提出了評估生產網絡整體績效之方法。在此方法的應用上，網絡中各企業的績效將決定於其對整體網絡的貢獻多寡。透過此方法，我們同時也看到，將整體生產網絡進行解構分析，管理者能發現更多可加以改善的細部環節，諸如生產效率與規模效率的改善。
- 在流程設計方法中，我們評量的是系統在未來，而非過去的績效。我們針對兩種不確定性環境，提出結合了 DEA、統計與模擬方法的設計架構。利用本方法，企業經營者可在不確定環境中，求出基於多目標的最佳設計參數。

我期待，並相信本文所提出的流程設計方法，在未來可廣泛施行於許多其他供應鏈問題上。

Nederlandse Samenvatting (Summary in Dutch)

Supply Chain Management (SCM) is uitgegroeid tot een van de meest belangrijke strategieën om bedrijfsprestaties en concurrentieposities te verbeteren. Echter, succesvol SCM vereist meer dan alleen slimme tactieken of een geoptimaliseerde stroom van producten en services: het is ook afhankelijk van de integratie van diverse processen met organisaties. De integratie en coördinatie van Supply Chain activiteiten kan niet van de een op de andere dag plaatsvinden. Dit vereist weloverwogen lange termijn planning, ontwerp, uitvoering en, meest belangrijk, geschikte methoden om prestaties te meten om zo het gehele proces te kunnen overzien en waar nodig is aan te passen. Onder de toenemende druk van klanten en concurrentie, moeten managers tegenwoordig steeds vaker ingrijpende, beleidsbepalende besluiten nemen en vooruitstrevend plannen, hetgeen directe and substantiële gevolgen heeft voor de toekomstige prestaties van het bedrijf. Om deze reden zal, om op lange termijn strijdvaardig te zijn, het bedrijf zich moeten richten op ontwerp, evaluatie en de daaruit volgende supply chain activiteiten.

In dit proefschrift, ontwikkelen we een methodologie om complexe productieprocessen te ontwerpen en te evalueren. De ontwikkelde evaluatiebenadering is gebaseerd op DEA (Data Envelopment Analysis) model door meerdere invoer en uitvoer productieparameters werden beschouwd. Om precies de prestaties van een

Supply Chain te analyseren, modelleren we de dynamische relaties tussen de productieprocessen van bedrijven. Met deze benadering kunnen zowel individuele bedrijven als productienetwerken op een systematische manier geëvalueerd worden. De resultaten van de evaluatie, betreffende entiteiten op verschillende niveaus, kunnen managers effectief assisteren bij het identificeren van kritieke punten voor verbetering. In het tweede deel van dit proefschrift ligt de focus op procesontwikkelingsmethoden voor verschillende situaties van beschikbaarheid van informatie. Deze methoden combineren evaluatiebenaderingen en simulatietechnieken om de prestaties van verschillende procesontwikkelingen of de mogelijk toekenning van financiële hulpmiddelen te evalueren. Ons methodologie heeft betrekking op managers binnen een beleidsvoerend proces voor betere flexibiliteit en toepasbaarheid op verschillende problemen en omgevingen. We illustreren onze methode met een analyse van de ontwikkeling van orderpikkende systemen en R&D project selecties.

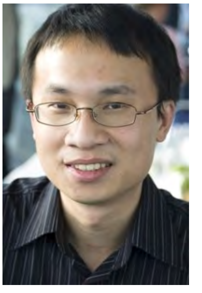
De bijdrage en resultaten van dit proefschrift kunnen samengevat worden tot:

- De ontwikkeling van een dynamisch DEA model om de dynamische efficiëntie van bedrijven te evalueren. In dit model zijn de productieprocessen van bedrijven in verschillende tijdsperiodes dynamisch aan elkaar gerelateerd. Onze empirische resultaten laten zien dat het gebruik van conventionele DEA modellen kan leiden tot significante verstoringen in de resultaten van de evaluatie van dynamische productiesituaties.
- In navolging van de concepten van dynamische DEA modellen, is een evaluatiebenadering ontwikkeld voor productienetwerken. De benadering kan gebruikt worden om bedrijven te evalueren op basis van hun bijdragen aan het productienetwerk. Er is aangetoond dat het afbreken van productieprocessen van supplynetwerken voor evaluatie, meer praktische inzichten kan geven in hoe supplynetwerkprestaties verbeterd kunnen worden in termen van technische of geschaalde efficiëntie.
- In plaats van het verleden te evalueren, moeten we bij procesontwikkelingsproblemen de toekomstige prestaties van bedrijfsprocessen evalueren. We

integreren DEA met simulatietechnieken en statistische methoden om procesontwikkelingsproblemen aan te pakken met twee verschillende informatieve aannames: risico- en onzekerheidsproblemen. Door gebruik te maken van onze benadering kunnen managers hun besluitvorming optimaliseren met slechts incomplete informatie over toekomstige omstandigheden.

De door ons voorgestelde methoden kunnen worden toegepast op een groot scala van andere problemen binnen supply chain planning, zoals capaciteitstoewijzing en ontwerp van logistisch processen.

About the author



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- Supply chain modeling.
- Operations research.

His “non”-research interests include:

- Oriental cuisine (on the receiving, not producing end).
- Reading and Music.

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EVALUATION AND DESIGN OF SUPPLY CHAIN OPERATIONS USING DEA

Performance evaluation has been one of the most critical components in management. As production systems nowadays consist of a growing number of integrated and interacting processes, the interrelationship and dynamics among processes have created a major challenge in measuring system and process performance. Meanwhile, rapid information obsolescence has become commonplace in today's high-velocity environment. Managers therefore need to make various decisions based on incomplete information about the future environment. This thesis studies the above problems in the evaluation and design of complex operation systems in a supply chain. Based on the widely used Data Envelopment Analysis (DEA) models, we develop a generalized methodology to evaluate the dynamic efficiency of production networks. Our method evaluates both the supply network and its constituent firms in a systematic way. The evaluation result can help identify inefficient firms in the network, which is crucial for improving the network performance. Part II of the thesis covers multi-criteria process design methods developed for two different situations of information availability. Our design approaches combine interdisciplinary techniques to facilitate efficient decision-making in risky and uncertain situations. As an illustration, we apply these approaches to warehouse planning and resource allocation problems in a supply chain.

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