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REVIEW ARTICLE

A UNIFIED FRAMEWORK FOR MANUFACTURING STRATEGY DECISION TO GAIN COMPETITIVE ADVANTAGES

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ABSTRACT

Manufacturing strategy research aims at providing a structured decision-making approach to improve the economics of manufacturing and to make companies more competitive. The overall objective of this paper is to investigate how manufacturing companies make use of different manufacturing practices or bundles of manufacturing practices to develop certain sets of capabilities, with the ultimate goal of supporting the market requirements. We propose a technique that can effectively take managerial preferences and subjective data into consideration, along with quantitative factors. The tool that is proposed here relies on the use of a more effective version of the Analytical Hierarchy Process (AHP) called the Analytical Network Process (ANP) to help integrate managerial evaluations into a more quantitatively based decision tool, data envelopment analysis (DEA). In this paper, these two techniques, when used together, can provide subjective and objective evaluations for manufacturing strategy decision makers. An illustrative example provides some insights into the application of this methodology. The research contributes to several insights to the research area of manufacturing strategy and to practitioners in manufacturing operations. A model that investigates process improvement investments, assuming that alternative process improvement initiatives exist, is then presented.

KEYWORDS

Analytical Hierarchy Process, Analytical Network Process, Manufacturing Strategy Decision, Data Envelopment Analysis.

1. INTRODUCTION

The overall and overarching goal of any company is long time survival and the ability to produce useful outputs. Manufacturing strategy is concerned with providing long term guidelines. In order to succeed with the goal of long-term survival and the ability to produce useful output manufacturing companies continuously make decisions regarding *e.g.* the deployment of resources. Irrespective of whether the decisions are conscious or not, they determine how the company is operated. By actively taking charge over the decisions the competitive position of a company can be shaped over time. In this, manufacturing strategy plays an integral part. Manufacturing strategy as a concept was first recognized by Skinner [1], referring to a manufacturing strategy as to exploit certain properties of the manufacturing function to achieve competitive advantages. Hayes and Wheelwright [2] describe manufacturing strategy as a consistent pattern of decision making in the manufacturing function linked to the business strategy. Swamidass and Newell [3] describe manufacturing strategy as a tool for effective use of manufacturing strengths as a competitive weapon for achievement of business and corporate goals. A more comprehensive definition of manufacturing strategy is provided by Platts et al. [4]: "a pattern of decisions, both structural and infrastructural, which determine the capability of a manufacturing system and specify how it will operate, in order to meet a set of manufacturing objectives which are consistent with the overall business objectives." [4]. Leong et al. [5] summarizes these into what has become the predominant model of manufacturing strategy content (Figure 1).

The model identifies two major constituents of manufacturing strategy content, competitive priorities and decision categories [5, 7]. These will be dealt with in the following sections.

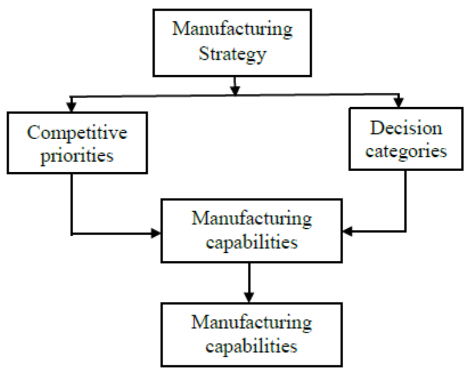

Figure 1: Manufacturing Strategy Model [6].

1.1 Competitive priorities

Competitive priorities defines the set of manufacturing objectives and represents the link to market requirements [2, 5, 7-9]. Dimensions commonly used are; cost, quality, flexibility, and delivery [2, 5, 10, 11]. While some studies suggests innovativeness and service as additional priorities empirical research and strategy theories consistently stress the four basic dimensions [12-15, 6]. The common set of competitive priorities with descriptions is presented in Table 1.

Table 1: Competitive Priorities with Descriptions.

Competitive priorities	Description
Quality	Manufacture of products with high quality and performance standards
Delivery	Reliable (on time) and fast (short delivery lead time) delivery of products
Cost	Production and distribution of the product at low cost
Flexibility	Ability to handle volume and product mix changes

Most researchers consider the competitive priorities part of manufacturing strategy as the link between market requirements and manufacturing [9, 11, 18]. Of particular interest is the relative weighting of different dimensions of competitive priorities. Among the competitive priorities there are often trade-offs inherent and to focus the attention to certain dimensions is the essence in the factory focus literature drawing on Skinner's [1] work. However, limiting the scope brings another problem, which dimensions to focus on. Hill [11] presented the concept of order winners and qualifiers related to the importance of competitive priority dimensions. Qualifying criteria (dimensions) are those that a company must meet for the product to even be considered in the market place. Common criterions considered qualifiers are conformance quality and delivery reliability. Order winning criteria are those that differentiate the manufacturer from its competitors and "win" the order. Although the concept of order winners and qualifiers provides a categorization and prioritization of competitive dimensions it gives a rather rough account. More precise is to rank requirements by relative weight. Hill [11] suggests apportioning 100 points between requirements.

1.2 Decision categories

Decisions in manufacturing related issues are often grouped into categories, usually denoted decision categories. Since Hayes and Wheelwright [2] first presented the concept numerous authors have contributed to the development and establishment of the set of decision categories, and associated policy areas, normally used. Leong et al. [5] provide a summary of a number of decision category frameworks in the literature and find that the division of categories into structural and infrastructural categories as proposed by Hayes and Wheelwright [2] still is valid and useful. Table 2 lists some examples of decision categories and associated policy areas, based on Leong et al. [5]. Similar descriptions can be found in *e.g.* Platts et al. [4] and Platts et al. [4].

As noted in the definition the operation of manufacturing strategy comes through a pattern of decisions. This observation acknowledges the influence from management on the development and performance of the system, although seemingly trivial it is a very important observation also noted by Hayes and Pisano [16]. Decisions within the manufacturing functions determine which resources to use, what routines to use,

Table 2: Examples of Decision Categories and Associated Policy Areas (Based on Leong et al. [5]).

Decision categories	Policy areas
Structural Process choice Facilities Capacity Vertical integration	Process choice, technology, integration Size, location, focus Amount, timing, increments Direction, extent, balance
Infrastructural Manufacturing planning and control Performance measurement Organization Quality	System design, decision support, Measurements, methods of measures Human resources, design Definition, role, tools

i.e. what practices to employ and emphasize in order to achieve the manufacturing objectives. The set of practices, resources, routines used ultimately determine the operating characteristics of the manufacturing system, *i.e.* the manufacturing capabilities [17].

1.3 Manufacturing capabilities

Manufacturing capabilities are characterized by the set of practices in use. The capabilities are formed by the objectives for the manufacturing system paired with the history of decisions in manufacturing related issues [6]. Also, dependent on the set of capabilities inherent in the system at hand different performance levels can be achieved, *i.e.* capabilities are the basis for operational performance. Thus, manufacturing capabilities can be viewed as the linkage between manufacturing strategy content and manufacturing performance as depicted in Figure 1. Manufacturing strategy has adopted the notion of capabilities from the strategic management literature, particularly the resource-based view (RBV) of the firm proposed by Wernerfelt [18] and Barney [19]. The basis in RBV is that resources are not uniformly distributed across firms and thus provides the potential of being a source to competitive advantage. Resources are referred to as assets, routines, practices *etc.* controlled by a firm that are valuable, rare, imperfectly imitable and unsubstitutable [19]. Hayes and Pisano [16] suggest that a company needs to differentiate itself from its competitors on the basis of something valuable to the customer. The way to do this is to harness the benefits of various improvement programs or bundles of practices, like Lean manufacturing or TQM, "in the service of a broader manufacturing strategy that emphasizes the selection and growth of unique operating capabilities" [16]. Corbett and Claridge [20] denote capabilities as the ability of a firm to apply resources to do something and further states that capabilities form the primary basis for competition between firms. In the manufacturing strategy literature, capabilities are often conceptualized as a business unit's intended or realized competitive performance or operational strengths [6, 14, 15, 21-24] and are therefore assessed using measures of operational performance, which typically includes cost, quality, flexibility, and delivery measures. Swink and Hegarty [25] suggest that the performance-based approach to capabilities is conceptually aggregated to clearly direct the proper use of manufacturing resources. Different from the performance-based approach to capability research that is dominating the manufacturing strategy literature is the routine based approach to explaining the heterogeneity of firms. Capabilities are identified as high-level routines or bundles of routines [26, 27].

1.4 Manufacturing performance

It is difficult to fairly assess manufacturing performance. Financial measures, such as ROI, profitability *etc.*, are usually plant level measures that are subject to many factors outside the scope of manufacturing

Table 3: Examples of Internal and External Measures of Operational Performance.

Operational performance dimension	Internal performance measures	External performance measures
Quality	Rework cost, percentage of passed quality inspection, cost of quality control	Conformance to agreed upon specification, product performance
Delivery	Production lead time, accuracy of inventory status, dependability of internal lead times	Delivery lead time, on-time deliveries, stock availability
Cost	Unit cost of manufacturing, inventory turnover, capacity utilization, yield	Product selling price, market price
Flexibility	Set up time/cost, length of fixed production schedule, amount of operating capacity,	Product range, number of products offered, ability to handle volume and product mix changes

operations. An attempt to isolate the performance of the operations function is to utilize measures where the management of operations plays an integral part, *i.e.* operational performance measures [14, 15, 28, 29]. Dimensions used conveniently coincide with the common set of competitive priorities, *i.e.* quality, delivery, flexibility and cost performance. Important to acknowledge is that every dimension, to some extent is vital for all operations, which one is the most important is just a matter of competitive positioning [30, 31]. Examples of measures are provided in Table 3.

1.5 Quality performance

Quality is a multifaceted term. According to Garvin [10] quality can be viewed from up to eight different perspectives; performance, features, reliability, conformance, durability, serviceability, aesthetics and perceived quality. Within manufacturing operations the conformance dimension is most influential since it refers to the process' ability to produce products to their predefined specification reliably and consistently [8, 13]. High levels of conformance quality must be attained before trying to improve any other of the performance dimensions [21, 32].

1.6 Delivery performance

The two main dimensions of delivery performance are delivery reliability and delivery speed [13]. Delivery reliability is sometimes referred to as dependability or on-time delivery and concerns the ability to deliver according to a promised schedule or plan. This sub dimension of operational performance is often regarded a prerequisite [33-35]. Delivery speed is concerned with the length of the delivery cycle. Ward et al. [13] argues that although the dimensions are separable, long run success requires that promises of speedy deliveries be kept with a high degree of reliability. There is a caveat with the delivery dimension, companies in different environments relate differently to both delivery speed and reliability. Delivery speed is, from a market perspective, the elapsed time from the receipt of a customer order to final delivery [36].

1.7 Flexibility performance

Flexibility is also regarded to be a multidimensional concept [10, 37]. D'Souza and Williams [38] define four dimensions of manufacturing flexibility; volume, variety, process and material handling flexibility. Further, they note that volume and variety are "mainly externally driven" towards meeting the needs of the market. Similarly, Suarez et al. [39] and Slack [40] proposes volume, mix, new-product, and delivery-time flexibility as those types that directly influence the competitive position of the company. Within existing manufacturing operations the most influential types are the ability to adjust manufacturing volume and the ability to change between products [41, 42].

1.8 Cost performance

Cost is an absolute term and measures the amount of resources used to produce the product. Slack and Lewis [8] stressed that all producers, even those whose primary source of competitiveness is different from product selling price will be interested in keeping their costs low. Every dollar removed from the operation's overall cost is a dollar added to the bottom line profits. Therefore cost performance is the most important of the different operational performance dimensions [8], although cost often is ranked least important in empirical studies [14].

Manufacturing strategy decisions are critical to a manufacturing organization's long term survival and well-being. Manufacturing strategy decisions (MSD) should be linked to strategic goals and objectives of the manufacturing organization. If they are to lower cost, financial considerations should be part of the manufacturing organizational strategic objective, if it is quality, then that needs to have a higher priority in the selection, design, and implementation of manufacturing projects. The issue is that a manufacturing strategy decisions should have a definite goal in mind, one that supports the strategies of the manufacturing organization. Manufacturing organizations typically are subsumed by four primary strategic considerations Cost, Quality, Flexibility and Speed (velocity, time). This argument is similar to one that is made for any strategic investment in a manufacturing organization. Yet, manufacturing strategic investments necessarily have to incorporate both qualitative and quantitative factors into their evaluation.

We propose a technique that can effectively take managerial preferences and subjective data into consideration, along with quantitative factors. The tool that is proposed here relies on the use of a more effective version of the Analytical Hierarchy Process (AHP) called the Analytical Network Process (ANP) to help integrate managerial evaluations into a more quantitatively based decision tool, data envelopment analysis (DEA). AHP has been frequently applied to these strategic decision environments, DEA has been used much more sparingly and ANP even less so. Together, ANP and DEA provide synergistic advantages, primarily through the integration of qualitative and quantitative factors. The presentation of this methodology will be within the context of selecting manufacturing strategy decisions. Even though we structure the methodology and example in the context of manufacturing strategy decisions alternatives, it can be generalized to other strategic decision making areas. This paper's flow will include a background and introduction of justification and evaluation of manufacturing strategic organizational projects, ANP and DEA. A model that investigates process improvement investments, assuming that alternative process improvement initiatives exist, is then presented. This model basis its goals and objectives on manufacturing strategic factors, which may then be evaluated on more operational measures. These operational measures will be used within a DEA based model that will help rank various manufacturing strategy decisions alternatives either for justification, selection or evaluation purposes. An illustrative example helps to present the concept of synergistically linking these two techniques. An evaluation of the usefulness of the techniques, advantages and disadvantages, especially with respect to manufacturing strategy decisions alternatives evaluation are then presented. Future directions for development and research are also presented in the final conclusions.

2. LITERATURE REVIEW

Since the first paper on manufacturing strategy by Skinner in 1969 the field has established itself as a well-defined research area. Manufacturing strategy has since received much attention, both within the academic communities but also from practitioners involved in the management of manufacturing operations. One of the main purposes of research on manufacturing strategy is identification of the drivers of high performance, and more recently the sustainability of competitive advantage [43]. The link between practice and performance (actions and outcomes) has been the focus for much of the manufacturing strategy research where the typical dependent variable has been some kind of measure of competitive performance, whether it is financial (*e.g.* ROI, market share) or operational (quality, delivery *etc.*) performance *vis-à-vis* competition. Practices studied range from very hands on (*e.g.* setup time reduction) to practices of a more conceptual nature (*e.g.* agile manufacturing). MacDuffie [44] and Shah and Ward [45] suggests using bundles of practices in order to better capture the inherent nature of wider, multidimensional manufacturing concepts such as *e.g.* lean manufacturing. Suresh et al. [46] suggest that a strategy planning process includes identifying "ends and ways" (business objectives and strategy) and developing "means" (resources and capabilities) by which the selected ends and ways can be realized. Similarly, Ward et al. [13] note that manufacturing strategy embodies the choices among the most needed set of manufacturing capabilities for a business unit and the investments required to build that set of capabilities. From a practical standpoint, it is central for managers to both understand the business and manufacturing objectives and to identify means to build and develop manufacturing capabilities that support these objectives. Over the years many concepts related to improving manufacturing capabilities have been advocated and put forward as the solution, as the key to improved performance and a sustainable competitive advantage. However, similar to the idiosyncrasy of individuals, companies are not a homogeneous group that responds equally to certain actions. Hence, there are no action plans, improvement programs or manufacturing concepts that are universally applicable due to differences in *e.g.* industry structure [47, 48] or strategic emphasis [49]. The impact from any one concept may therefore vary significantly dependent upon the situation into which it is applied. Ketokivi and Schroeder [43] find an important challenge in justifying and examining why and under which conditions certain actions have competitive value. In essence, fitting a manufacturing plant's practices and routines to its environmental, structural and strategic context is crucial to developing operations as a competitive advantage [47-51]. The relationships among manufacturing capabilities have been the locus for much attention in operations management research. Typically, the research involve assessing the operational performance [13], identifying the relationships among different operational performance dimensions [21, 32, 52], or understanding the linkage between operational performance and business and manufacturing strategy [53, 54]. Underlying theories has been the well-known trade off theory initiated by Skinner [1] and the more recent notion of cumulative capabilities [21, 32]. Although the area has received much attention, there still exist differences in opinion within the academic community as to the relationships among and between different dimensions of manufacturing capabilities. Further, Swink and Way [55] describe identification of contingencies which favor the development of cumulative capabilities as one of the important challenges for future research in operations strategy. Contingency variables tested so far include country (*e.g.* Noble [22], industry [20], process choice [56], and strategic emphasis [6]. The scope of this paper is concerned with operational performance of manufacturing companies and the relationships between on the one hand, different dimensions of operational performance and on the other, how certain practices or bundles of practices impact operational performance. Four basic dimensions of operational performance are treated in this paper; quality performance, delivery performance, cost performance and finally, flexibility performance. The paper also investigates contingencies, structural and strategic, that may influence the impact on and relationships between operational performance dimensions. Sometimes the selection of process improvement comes after investigation and evaluation of hard technology investments. This may be due to many reasons including 1) technophilia: the love of technology for technology's sake; 2) engineers focusing on technological rather than process breakthroughs; or 3) it is easier to justify hard technologies to financial analysts. According to Bollen [57] the development of a "process discipline" is essential in helping firms make better capital investment decisions. They argue that investments in technological solutions can be expensive and may even be detrimental to the operations of the facility if process improvement is not initially implemented. This is the same argument as seeking simplifications first, automate processes, then integrating, (i.e. simplify, automate, integrate) [58]. The managerial argument is that hard technological investments should only occur after the process improvements have been introduced into the manufacturing organization. Thus, manufacturing strategy decisions alternatives selection is not only important for the business process at hand, but also for any future strategic technological decisions. It is critical that tools for strategic analysis and justification are developed and applied to the BPI selection process. According to Popoff & Brache [59], a mistake in business process improvement projects is the development of a process-improvement plan without relating it to the strategic issues being faced by the business. They argue that process-improvement efforts that are not driven by a measurable strategic issue lose the support of top management and of the worker-level teams. Measurement of how many processes have been documented or how many teams have been formed do not add value to the manufacturing organization. Within this context, choosing the right processes to re-engineer and the appropriate overall scope of the reengineering effort has also caused difficulties. Process improvement selection to fit "technology", such as groupware, for example, may be a reason for unsuccessful BPI projects [60]. The relationship and arguments for evaluation and justification of strategic technologies with that of manufacturing strategy decisions alternatives is quite evident. Primarily, both impact, and should be linked to, manufacturing organizational strategy, and both require some form of qualitative and quantitative evaluation. Information technology (IT) is one technology most closely related to manufacturing strategy decisions alternatives. Studies have also shown that traditional appraisal techniques are no longer appropriate in justifying investments in IT because of the nature of intangible benefits, complexity of direct and indirect cost implications [61]. Thus, there is a need for more appropriate methods that can effectively integrate several performance measures into the decision making process. The number of models that are available and specifically targeted to selection and evaluation of manufacturing strategy decisions alternatives evaluation is quite limited [62-64]. Partovi's [63] is primarily targeted as an AHP benchmarking tool for processes, and is not explicitly targeted for selection, even though it may be used for that purpose. Feather (1998) is a process and very subjective tool for evaluation of manufacturing strategy decisions alternatives and selection. Presley et al. [64] provide a thorough, but relatively complex approach that does bring subjective and objective measures together, it is very data dependent, and does not analytically seek to determine the best solution or rank them. The number of models and tools available for strategic justification of programs, which include technologies, systems, supplier/partner selection, product development, and project selection, provide the foundation for the work presented in this paper. General issues relevant to this area of modeling and research have appeared in the broad and interdisciplinary literature. Firstly, evaluation and justification of strategic programs is part of a larger framework. This framework includes formation of a strategic plan and vision for the organization, planning (design) and analysis of "As-Is" and "To-Be" situations, determination of alternatives, evaluation and justification of alternatives, implementation, and monitoring and control [65]. Each of these stages has its own set of research issues, agendas and themes. Secondly, one of the more important concerns of the evaluation and justification literature and research is the over reliance on single factors (usually financial) and may provide results that may not be satisfactory to the long run survival of an organization. Thus, the models that have been introduced for evaluation purposes seek to consider multiple dimensions and factors that would aid decision-makers. Also, these factors need to be tied in to the long run strategic goals and performance measures of any organization. Example strategic justification frameworks that have been proposed for evaluating advanced technology and programs include those by Mohanty [66], Sarkis & Lin [65], and Suresh & Kaparthi [67]. Each of these frameworks provides a series of phases that include the integration of organizational and manufacturing strategy into the decision process. This integration of corporate and manufacturing strategy decisions alternatives into evaluation and justification decision making is still a practical issue with many organizations. One of the more popular techniques, based on the multiple dimensions of addressing most strategic decisions, is the analytical hierarchy process (AHP). AHP is used in the context of developing weightings for various tangible and intangible criteria [68-70]. Recently, the use of DEA has been proposed as a technique to evaluate technologies and programs within organizations [71-75]. Even though some of the techniques consider multiple criteria, most have relied on only one modeling approach. A recent extension for much of this work includes the use and synthesis of multiple techniques for evaluation of strategic programs. Recent techniques that have used multiple approaches for evaluation include those by [72, 76-80]. Many of these techniques involved the use of weight or preference elicitation through utility evaluation and analytical modeling approach and simulation. The decision framework presented here builds on the multi-phase, multi-objective model synthesis exemplified by these papers.

The framework will rely on an initial evaluation of the major factors and their relative importance and influences on the objectives of the manufacturing strategy decisions. This will be accomplished through the use of the Analytical Network Process (ANP). The second phase will take results of these factors and help to set restrictions and constraints on these factors in DEA. The integration of these two approaches is relatively new and has not been previously pursued. The advantages of using these two approaches synergistically, are that they integrate managerial preferences and data within an analytical approach that helps to evaluate a set of alternatives, with the outcome being a ranking of the these alternatives. An evaluation of these two tools using a manufacturing strategy decisions alternatives selection example provides some insights. Initially, quick and brief reviews of ANP and DEA are provided.

3. THE MODEL

3.1 The analytical network process

In multi-attribute decision making, the problem is to choose that alternative which most strongly fulfills the entire set of objectives. Simplifying assumptions in order to use quantitative techniques do not accurately reflect the complex situations sometimes found in decision environments, especially when strategic factors play a role in the decision. To be more practical, models should attempt to include and measure important tangible and intangible, quantitatively measurable, and qualitative factors. To be able to model these complex situations Saaty [81] has introduced the analytical hierarchy process (AHP). More recently, a more general form of the AHP approach, which incorporates feedback and interdependent relationships among decision attributes and alternatives, has been proposed as a more accurate approach for modeling complex decision environments. This technique has been described as the analytical network process (ANP) [82]. The ANP technique is not nearly as prominent in the literature as the AHP technique. ANP is an attractive multi-criteria decision making tool because it allows for the consideration of interdependencies among and between levels of attributes. ANP does involve representing relationships hierarchically but does not require a strict hierarchical structure as does AHP. ANP models problems of systems in which the relationships between the levels are not easily represented as higher or lower, controlling and subordinate. These systems are known as "systems-with-feedback" and refer to systems where a level may both dominate and be dominated, directly or indirectly, by other decision attributes and levels. The work on systems-with-feedback is extended to show how to study inner and outer dependence with feedback. Outer dependence is the dependence between components but in a way to allow for feedback circuits. Inner dependence is the interdependence within a component combined with feedback between components [83]. The ANP technique has had only a handful of applications in the research literature [74, 76, 83-85]. Many of the recent advances, and some additional applications, may be found in a recent book by Saaty [86]. Most of the modeling and decision frameworks in AHP and ANP can be described graphically. For example, in the AHP approach there are one-way hierarchical arcs that show a dominance or control of one level of attributes over another set of sub-components or attributes. In the ANP approach, with the allowance of interdependencies occurring among attributes and attribute levels, the graphical representation may include two-way arrows (or arcs) among levels. A looped arc is used to show the interdependency relationships that occur within the same level of analysis. The directions of the arcs signify dependence, arcs emanate from an attribute to other attributes that may influence it. As we have mentioned, the elements of the ANP system may interact along many paths. The supermatrix that is derived in the ANP approach, and described in more detail in the case example, helps to evaluate this framework.

3.2 Data envelopment analysis and efficiency models

(1) The basic CCR model

Charnes, Cooper, & Rhodes [87] proposed the initial data envelopment analysis (DEA) model, referred to as the CCR model, for evaluating the relative efficiencies of a homogenous set of decision making units (DMUs). The CCR model incorporates multiple inputs and outputs in evaluating the relative efficiencies of alternative DMUs, where efficiency can be defined as the ratio of weighted output to input. In this paper a DMU will be manufacturing strategy decisions alternatives to be introduced by a manufacturing unit. Using the notation of Doyle & Green [88], the general efficiency measure that is used by DEA can best be summarized by equation (1).

$$E_{ks} = \frac{\sum_y O_{sy} v_{ky}}{\sum_x I_{sx} u_{kx}} \tag{1}$$

where:

(E_{ks}):is the efficiency or productivity measure of manufacturing strategy decisions alternatives, using the weights of "test" manufacturing strategy decisions alternatives *k*, where the test manufacturing strategy decisions alternatives is the unit whose efficiency is to be evaluated;

(O_{sy}): is the value of output *y* for manufacturing strategy decisions alternatives;

(I_{sx}) is the value for input *x* of manufacturing strategy decisions alternatives;

(v_{ky}): is the weight assigned to manufacturing strategy decisions alternatives *k* for output *y*; and

(u_{kx}): is the weight assigned to manufacturing strategy decisions alternatives *k* for input *x*.

For the basic CCR model, the objective is to maximize the efficiency value of a test manufacturing strategy decisions alternatives *k*, from among a reference set of manufacturing strategy decisions alternatives *s*, by selecting the optimal weights associated with the input and output measures. The maximum efficiencies are constrained to 1. The formulation is represented in expression (2).

$$\text{Maximize } E_{kk} = \frac{\sum_y O_{ky} v_{ky}}{\sum_x I_{kx} u_{kx}}$$

subject to:

$$\begin{aligned} & E_{ks} \le 1 \quad \forall \\ & u_{kx}, v_{ky} \ge 0 \end{aligned} \tag{2}$$

This non-linear programming formulation (2) is equivalent to the following linear programming formulation (3):

$$\text{Maximize } E_{kk} = \sum_y O_{ky} v_{ky}$$

subject to:

$$\begin{aligned} & E_{ks} \le 1 \quad \forall \\ & \sum_x I_{kx} u_{kx} = 1 \\ & u_{kx}, v_{ky} \ge 0 \end{aligned} \tag{3}$$

The transformation is completed by constraining the efficiency ratio denominator from (2) to a value of 1. This is represented by the constraint $\sum_x I_{kx} u_{kx} = 1$ .The result of formulation (3) is an optimal "technical efficiency" value (E_{kk}*) that is at most equal to 1. If E_{kk}* = 1, then it means that no other manufacturing strategy decisions alternatives is more efficient than manufacturing strategy decisions alternatives *k* for its selected weights. That is, E_{kk}* = 1 has manufacturing strategy decisions alternatives *k* on the optimal frontier and is not dominated by any other manufacturing strategy decisions alternatives. If E_{kk}*< 1 then manufacturing strategy decisions alternatives *k* does not lie on the optimal frontier and there is at least one other manufacturing strategy decisions alternatives that is more efficient for the optimal set of weights determined by (3). The formulation (3) is executed *s* times, once for each manufacturing strategy decisions alternatives. Since, the Basic DEA Model may provide a number of alternative manufacturing strategy decisions alternatives' that are efficient. It would be difficult for a decision-maker or organization to decide on a single manufacturing strategy decisions alternative if there are more than one efficient units. Many of these efficient units occur when the basic CCR approach is used. To help discriminate among efficient manufacturing strategy decisions alternatives' and to help rank these manufacturing strategy decisions alternatives', DEA ranking approaches may be used. One such approach is recommended here.

(2) A ranking DEA model

A DEA approach that helps for ranking is a variation of the CCR model proposed by Andersen & Petersen [89]. In their model, they simply eliminate the test unit from the constraint set. The new formulation is represented by (4).

$$\text{maximize } E_{kk} = \sum_y O_{ky} v_{ky}$$

subject to:

$$\begin{aligned} & E_{ks} \le 1 \quad \forall \quad \text{BPI} \quad s \ne k \\ & \sum_x I_{kx} u_{kx} = 1 \\ & u_{kx}, v_{ky} \ge 0 \end{aligned} \tag{4}$$

Expression (4), which we will call the "reduced" CCR (RCCR) formulation, allows for technically efficient scores to be greater than 1. This result will allow for a more discriminating set of scores for technically efficient units and can thus be used for ranking purposes.

(3) Integrating managerial preference into the DEA ranking approach

Constraining the "flexibility" or range of weights (**u** and **v**) provides an approach for integrating managerial preferences into the RCCR models. The use of assurance regions (AR) for restriction of weights is one approach to better map managerial preferences to DEA. The concept of AR is described in detail by Thompson, et al. [90]. The process of setting AR begins with by defining upper and lower bounds for each input and output weight. The upper and lower bounds for each weight can help define constraints that relate the weight values of various factors. These LB and UB values may be ranges for preference weights for each of the factors (in this paper, operational measures) as defined by the decision-makers. The AR constraints relate the weights and their bounds to each other. The generalized AR constraint sets that are derived from *LB* and *UB* data are:

$$v_i \geq \frac{LB_i}{UB_j} v_j \text{ and } v_i \leq \frac{UB_i}{LB_j} v_j \tag{5}$$

These constraints can be added to expression (4) to form the RCCR with assurance regions (RCCR/AR) model. From a computational perspective, the number of additional constraints required to help define the AR is equal to $\frac{I*(I-1)}{2}+\frac{O*(O-1)}{2}$, where I and O represent the number of inputs and outputs, respectively.

4. EVALUATION FRAMEWORK AND ILLUSTRATIVE EXAMPLE

The synergistic framework presented in this paper is summarized in Figure 2. This framework is meant to fit within a broader "management of technology" process where strategic goals and objectives of the manufacturing organization are clearly delineated. As well, it is assumed that some analysis has been carried out for potential manufacturing strategy decisions alternatives. This analysis could be completed through some form of simulation or modeling effort, or even through estimation processes, for possible outcomes. This selection process is meant to occur after manufacturing strategy decisions alternatives have been determined. This framework provides rankings for the manufacturing strategy decisions alternatives. The next steps in the general process are to implement, maintain, and audit the performance of the selected manufacturing strategy decisions alternatives. The framework presented here may be a valuable tool in completing an audit, but the focus of this paper will be its application as a selection tool.

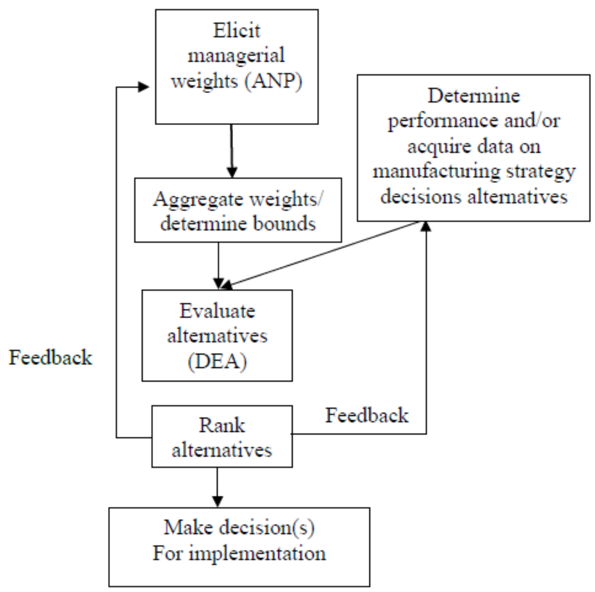

Figure 2: Manufacturing Strategy Decisions Alternatives Selection/ Ranking Framework

Within this model, weights from managerial insights into the various factors of the ANP models need to be determined. We shall assume that more than one user, decision maker, etc., is involved in the decision process. The next step in the process is to aggregate these weights. Even though the aggregation can be completed as a group decision making effort, we assume that each decision maker goes through the ANP approach. The decision maker weights provide the bounds for the DEA assurance regions. That is, upper and lower bounds will be determined from the ranges of the manager importance weights for the operational measures. A couple of approaches may be used to determine the ranges. One approach is to take an average and use some standard deviation measure to provide the ranges for the weights. The other approach would be to use maximum and minimum weighting scores for assurance region limits. The answers may come out differently depending on the distribution of the responses. The use of statistical ranges may be dependent on the number of decision makers. We will assume the minimum and maximum weighting scores, since; in many cases the number of decision makers in an organization is limited. As part of this framework, we will have to assume that operational measurement performance data for the manufacturing strategy decisions alternatives is available. This assumption is not trivial and may require significant effort by analysts to acquire this information. The use of simulation, modeling, benchmarking and estimation tools will have to be used in this situation, since the selection needs to be made before the actual implementation. Afterwards, in the auditing stages, this same framework can integrate actual post-implementation data to evaluate the performance of manufacturing strategy decisions alternatives among each other. The DEA evaluation is then completed, integrating both the performance data and managerial preference bounds. The results will be a ranking of the alternatives based on relative efficiency scores, using the RCCR/AR model. Sometimes, going through the decision process, analysts and decision makers learn more about the alternatives, factors and process. Thus, a feedback loop is included to help managers structure their decision more effectively and to allow for sensitivity analysis. There can be several potential manufacturing strategy decisions alternatives that a manufacturing firm can consider for implementation. Manufacturing strategy decisions alternatives can involve a combination of strategic, tactical, and operational level alternatives. Strategic level alternatives include locating and acquiring new facilities and/or expanding existing facilities, extent of vertical integration, etc. Tactical level alternatives involve advanced manufacturing technology choices, facility layouts, work-center configuration options, etc. Operational level alternatives are scheduling and sequencing methods, statistical process control techniques, and other shop-floor control methods. It is quite evident that even with few alternatives at each level there will be a significant number of manufacturing strategy decisions alternatives options that must be considered by management. To illustrate the proposed framework, a total of 10 potential manufacturing strategy decisions alternatives are considered for evaluation.

4.1 Description of Analytic Network Process (ANP) decision network hierarchy

In the illustrative example, we shall assume that a manufacturing organization is competing in a very volatile market. New products appear, and discontinue relatively quickly, but some may grow and maintain large customer bases. It is in this simplified environment that the managers need to make decisions concerning manufacturing strategy projects. The decision network hierarchy developed for this decision environment, to help elicit managerial preferences, includes four major elements (as shown in Figure 3). The simple objective of the decision network hierarchy, for the sake of this framework, is to elicit managerial weights, based on the strategic mission of the manufacturing organization, which can be integrated into the latter portions of the analysis. Thus, three levels of decision clusters exist (other than the objective). One cluster includes the major strategic categorical measures the manufacturing organization uses to determine its overall performance, especially from a manufacturing perspective. The operational measures that can be used to help evaluate the manufacturing strategic performance in these categories are the next cluster. The last cluster is a temporal relationship of these measures. The planning horizon cluster allows for a more dynamic environment to be considered. The relationships of the clusters to each other are shown in Figure 3 at a higher level of abstraction. This

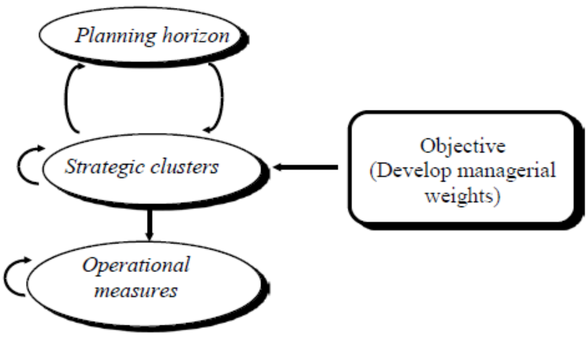

Figure 3: High Level Diagrammatic Representation of Network Decision Hierarchy for Managerial Weights Elicitation.

Figure 3 shows the various dependencies and interdependencies among the various clusters (by the arcs and arrows). For example the overall managerial objectives are dependent on the evaluation of the strategic categories.

The strategic categories and their relative importance levels have an interdependent relationship among each other and the temporal, planning horizon, cluster. The interdependent relationships will be described in more detail, once the clusters are further defined. There is only a one way relationship dependence between the operational measures and the strategic clusters. This one way relationship essentially states that the strategic measures are composed of operational measures that are influenced (controlled) by the upper strategic measures. To make sure convergence occurs in the final supermatrix, it is assumed that each operational measure has an internal dependency. According to Saaty [86], this characteristic does not change the final solution, but is only included for mathematical expediency. The next level of detail (Figure 4) more clearly delineates the relationships among the decision network hierarchy. Firstly, the strategic clusters. The literature is profuse with various general strategic performance measures that can be used to evaluate a manufacturing organization. These major categories from the literature include Quality, Delivery, Cost, and Flexibility, or some variation thereof [2, 69, 74, 78]. The strategic performance measures may also influence each other (internal interdependencies). For example, flexibility may be impacted more by quality measures and cost reduction measures, then by time measures and actions. These interdependent relationships are allowed to adjust the overall importance of some of the factors.

Another fine tuning of the ultimate preference weighting scheme occurs during consideration of the relationships among the strategic factors and the planning horizon. In this example, the planning horizon is categorized into short term and long term time ranges. The network model could have used actual time length (e.g. years) or location in a product's life cycle (e.g. growth, maturity decline) clusters to incorporate the dynamic temporal effects on manufacturing or organizational strategy. In this example, short term planning may put more emphasis on flexibility and time, than on cost measures (i.e., getting the product out quickly and making rapid changes is more important than minimizing costs), but in the long term, quality and cost (to maintain market share) may be more important. Also, a strategic factor may change in its own importance over time periods. For example, focusing on short run costs may be more important to the organization than a focus on long run costs. This interdependency is evaluated in the supermatrix. The final relationships are the operational measures' dependency on the strategic clusters that are selected. To maintain simplicity in the illustrative example, while still presenting the robust capabilities of the decision framework, only

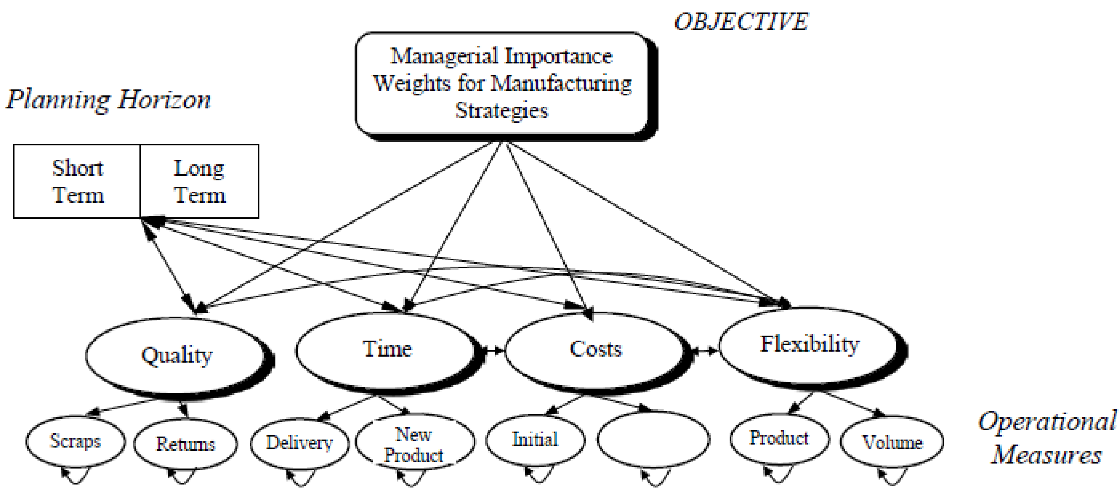

Figure 4: Detailed Level Diagrammatic Representation of Network Decision Hierarchy for Managerial Weights Elicitation.

two operational measures will be introduced for each cluster. These operational measures will be the "inputs" and "outputs" to be used to evaluate the alternatives in the DEA model.

4.2 Weight and bounds determination

To determine the managerial weights, each set of relationships needs to have pair-wise comparisons completed. The relative efficiency scores are then aggregated into a supermatrix. Whereupon, a stable set of weights are determined, by "converging" the supermatrix. We will show the example of only one managerial decision maker's supermatrix, and assume the upper and lower bounds that need to be determined from the whole set of decision makers. The first step in the ANP process is similar to calculating relative preference weights among factors, using traditional AHP. That is, a pair-wise comparison matrix is developed where the relative importance of each of the factors, when evaluated with respect to the "controlling" factor, are determined. Table 4 shows the pair-wise comparison matrix for the major strategic clusters based on the organizational objective (the controlling factor).

Table 4: Pairwise Comparison Matrix and Relative Importance Weight Results for Strategy Clusters and Impact on Objective for Illustrative Example.

Supp. Sel.	Finan.	Tech.	Qual.	Flexibility	w
Finan.	1	2	1/3	3	0.27
Tech.	1/2	1	1/6	1/2	0.02
Qual.	3	6	1	6	0.54
Flexibility	1/3	2	1/6	1	0.10

(1) Eigenvector, relative importance weights, calculation methodology

Saaty [81] has recommended a scale of 1 to 9 when comparing two components, with a score of 1 representing indifference between the two components and 9 being overwhelming dominance of the component under consideration (row component) over the comparison component (column component). If a component has some level of weaker impact,

Table 5: Initial Supermatrix for Illustrative Example Network Hierarchy.

	OBJ	ST	LT	Qual	Delivery	Cost	Flex	Yd	Ret	Ini	Rec	Dlv	NP	Prod	Vol
Objective	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Short Term	0	0	0	0.4	0.35	0.7	0.6	0	0	0	0	0	0	0	0
Long Term	0	0	0	0.6	0.65	0.3	0.4	0	0	0	0	0	0	0	0
Quality	0.47	0.10	0.38	0	0.25	0.25	0.4	0	0	0	0	0	0	0	0
Delivery	0.16	0.10	0.41	0.35	0	0.35	0.4	0	0	0	0	0	0	0	0
Cost	0.30	0.44	0.13	0.35	0.3	0	0.2	0	0	0	0	0	0	0	0
Flexibility	0.09	0.35	0.09	0.3	0.45	0.4	0	0	0	0	0	0	0	0	0
Yield	0	0	0	0.65	0	0	0	1	0	0	0	0	0	0	0
Returns	0	0	0	0.35	0	0	0	0	1	0	0	0	0	0	0
Initial	0	0	0	0	0.4	0	0	0	0	1	0	0	0	0	0
Recurring	0	0	0	0	0.6	0	0	0	0	0	1	0	0	0	0
Delivery	0	0	0	0	0	0.7	0	0	0	0	0	1	0	0	0
New Product	0	0	0	0	0	0.3	0	0	0	0	0	0	1	0	0
Product	0	0	0	0	0	0	0.7	0	0	0	0	0	0	1	0
Volume	0	0	0	0	0	0	0.4	0	0	0	0	0	0	0	1

Table 6: Converged Supermatrix for Illustrative Example Network Hierarchy.

	OBJ	ST	LT	Qual	Del	Cost	Flex	Yd	Ret	Ini	Rec	Dlv	NP	Prod	Vol
Objective	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Short Term	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Long Term	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Quality	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Delivery	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Cost	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Flexibility	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Yield	0.19	0.13	0.18	0.3	0.1	0.1	0.1	1	0	0	0	0	0	0	0
Returns	0.10	0.07	0.1	0.2	0.1	0.05	0.1	0	1	0	0	0	0	0	0
Initial	0.09	0.09	0.12	0.1	0.2	0.07	0.1	0	0	1	0	0	0	0	0
Recurring	0.14	0.13	0.19	0.1	0.3	0.11	0.1	0	0	0	1	0	0	0	0
Delivery	0.19	0.21	0.15	0.1	0.1	0.34	0.1	0	0	0	0	1	0	0	0
New Product	0.08	0.09	0.06	0.1	0.1	0.14	0.1	0	0	0	0	0	1	0	0
Product	0.14	0.19	0.13	0.1	0.1	0.12	0.3	0	0	0	0	0	0	1	0
Volume	0.07	0.1	0.07	0.1	0.1	0.07	0.2	0	0	0	0	0	0	0	1

the range of scores will be from 1 to 1/9, where 1 represents indifference and 1/9 being an overwhelming dominance by a column element over the row element. When scoring is conducted for a pair, a reciprocal value is automatically assigned to the reverse comparison within the matrix. That is, if a_{ij} is a matrix value assigned to the relationship of component i to component j, then a_{ji} is equal to $\frac{1}{a_{ij}}$ (or $a_{ij}a_{ji}$= 1). Once the pair-wise comparisons are completed, the local priority vector w (defined as the evector in the example figures) is computed as the unique solution to:

$$Aw = \lambda_{\max} w, \tag{6}$$

Where $_{\max}$ is the largest eigenvalue of A. These calculations were completed using the "Automan" software for AHP analysis of advanced manufacturing technology [90]. The results of this pair-wise comparison matrix show that quality is viewed, by this decision maker, to be the most important strategic factor (0.47), while flexibility is perceived as least important for the strategic goals of the manufacturing organization. The relative importance weights of this matrix (evector) are then introduced into the supermatrix (Table 5). The evector for the strategic clusters relative importance on the objectives of the manufacturing organization (from Table 5) are shown in bold numbers in Table 5.

To complete the supermatrix a total of 15 pair-wise comparison matrices need to be evaluated. One for the strategic cluster-objective relationship, 4 for the strategic cluster interdependencies, 6 for the interdependencies between the planning horizon and strategic clusters, and 4 for the operational measures-strategic clusters relationships. Many of these pair-wise comparison matrices contained only 2 factors, thus requiring only one comparison to be made. In more complex situations the number of comparisons may increase geometrically. As we can see in the supermatrix in Table 5, this decision maker views time and flexibility to be relatively more important than quality and cost in the shorter term planning horizon. The opposite seems to be

Table 7: Upper and Lower Bounds of Relative Importance Weights for Operational Measures in the Illustrative Example.

Factor	Lower Bound	Upper Bound
Yield	0.10	0.220
Returns	0.096	0.187
Initial	0.092	0.210
Recurring	0.078	0.145
Delivery	0.091	0.185
New Product	0.079	0.124
Product	0.082	0.191
Volume	0.071	0.180

true for the long term planning horizon. As well, a similar pattern exists in terms of where to put relative emphasis for each of the factors. This decision maker thinks long term quality and long term cost management should be the focus, while short term flexibility and time concerns play a dominant role. For the various operational measures this manager believes that: yield (0.65) has more influence than returns (0.35) on quality measurement; recurring costs are more important than initial costs; delivery more important than new product introduction time; and product flexibility more important than volume flexibility. Notice that the various operational measures form an identity submatrix for its components. This characteristic exists so that the whole network hierarchy model can be introduced into a single supermatrix that is convergent. Another approach would be to only consider the portions of the supermatrix where a "closed" loop exists, and then adjusting the remaining weights of the hierarchy with the weights from the controlling elements determined from the supermatrix calculation. This process would mean separating the analysis for the operations measures-strategic clusters, from the remainder of the supermatrix, thus reducing the size of the supermatrix. These operational measures can then be integrated by multiplying their relative importance scores to the scores from the supermatrix (see Azhar & Leung [84] for an example of this separation and calculation). The full network is evaluated in the supermatrix in this example. The next step in the ANP process is to determine a set of converged relative importance measures for the operational measures from the supermatrix. This convergence may be completed by raising the supermatrix to a sufficiently large power. In this case the convervengce to at least the fourth decimal place (10^{-4}) occurred when the matrix was raised to the 32^{nd} power. The results of the converged supermatrix are shown in Table 6. This convergence and the final weights take into consideration all the various levels and relative importance weightings.

The weights from other managerial decision makers are then acquired. In this illustration, we shall assume that maximum and minimum values for each factor from among all the decision makers provide bounds for the assurance regions, which are to be used in the next phase of the framework. The results of the bounds for the eight operational measurement factors are shown in Table 7. For some factors, there seems to be tighter bounds, (e.g. new product), which means greater agreement by managers on the importance of these operational measures. Looser bounds mean more uncertainty and inconsistency in the importance of the measures. Further refinement and feedback may provide tighter bounds for later analyses.

4.3 DEA Evaluations

In this step we evaluate the performance of manufacturing strategy alternatives using DEA models and the factor weight restrictions derived from the ANP technique. Normally in DEA, inputs encompass any resources utilized by decision making unit (DMU)s, and outputs include actual number of products produced to a range of performance and activity measures. It is also a common practice in DEA to use measures with which "less is better" as inputs and "more is better" as outputs. Based on this definition of inputs and outputs, we have selected a total of 5 inputs and 3 outputs with two measures representing each of the four manufacturing strategic measures or competitive priorities: cost, flexibility, quality, and speed. The two cost measures considered are initial costs, which mainly include fixed costs associated with acquiring new technologies and systems for process improvement, and recurring costs which involve operating and maintenance costs. These two cost measures are utilized as two separate inputs. Flexibility measures considered in our analysis comprise of product and volume flexibility. Product flexibility is represented by the number of product options that can be produced, and volume flexibility is represented by the number of units that can be manufactured in a given time frame. These flexibility measures are treated as two outputs. Quality measures utilized in our study include yield rates and product returns. Yield rates represent the percentage of products that meet the internal requirements and pass inspection, and product returns provide a measure for non-conformities that are returned by the customer. While yield rates are considered as an output, the product returns operational measure is treated as an input. Finally, the two operational measures used for time are lead time for product delivery and time to market for new product. Both these measures are utilized as inputs. The data utilized in the illustrative example are shown in Table 8. This data is randomly generated from predefined distributions. The distribution ranges are shown in the legend of Table 8. This data set was mean normalized to eliminate any scale effects of the weight restrictions.

*IC - Initial costs expressed in thousands of $ -randomly generated from (70, 200)

RC - recurring costs expressed in thousands of $ -randomly generated from (15, 35)

PR - percentage of products returned -randomly generated from (0, 1)

LT - lead time for product delivery expressed in days -randomly

Table 8: Data for RCCR/AR Execution of Framework.

	Input 1	Input 2	Input 3	Input 4	Input 5	Output 1	Output 2	Output 3
Manufacturing Strategy Plan	IC*	RC*	PR*	LT*	TM*	PF*	VF*	YR*
1	88	28	0.06	4	6	7	8	62
2	82	26	0.34	7	5	6	6	85
3	85	22	0.84	3	8	5	8	88
4	75	25	0.26	2	5	8	6	75
5	88	28	0.23	5	8	5	9	86
6	66	25	0.84	6	9	9	7	83
7	93	23	0.78	8	5	8	8	85
8	90	25	0.08	2	6	6	9	85
9	98	26	0.85	8	6	5	8	85
10	94	27	0.82	7	8	6	6	88

Table 9: Results of DEA Analysis for Manufacturing Strategy Projects.

Manufacturing Strategy Project	CCR	RCCR	RCCR/AR
1	0.860	0.660	0.611
2	1.000	1.123	0.685
3	0.754	0.884	0.445
4	1.000	1.165	0.984
5	0.883	0.945	0.656
6	1.000	1.234	0.646
7	1.000	1.112	0.640
8	1.000	2.000	1.654
9	1.000	1.018	0.645
10	1.000	1.056	0.654

generated from (2, 10)

TM - time to market new product expressed in weeks -randomly generated from (5, 10)

PF - product flexibility (number of product options) -randomly generated from (5, 10)

VF - volume flexibility (max number of units that can be produced) expressed in hundreds -randomly generated from (6, 10)

YR - yield rate expressed as a percentage -randomly generated from (70,100)

In the execution of the DEA models, three separate models were run to show the variations in the results as managerial preferences are included. Initially, CCR evaluations are conducted and these results are depicted in Table 9. The CCR model identified projects 2, 4, 6, 7, 8, 9, and 10 to be efficient with a relative efficiency score of 1.000. The other three projects are considered to be inefficient. The CCR model, in this case, proves to be a poor discriminator among alternative projects. The decision maker is still left with the dilemma of choosing one from the seven efficient projects.

To better discriminate from among the efficient projects a RCCR model is executed. Among the efficient projects, the RCCR model identified manufacturing strategy project 8 to be the best performer with a score of 2.000 (in Column 3 of Table 9). However, this RCCR model fails to include the decision makers' preferences. To show the sensitivity of the preferences, the RCCR/AR model is executed. The AR's for this decision environment are chosen from the ANP analysis described in the previous section. The RCCR/AR model also identified manufacturing strategy project 8 (see column 4 of Table 9) to be the best performer, but it provides a different ranking of the projects when compared to CCR and RCCR models. For example, the second best performer according to RCCR/AR model is manufacturing strategy project 4, which is different from the other two models. This ranking of projects proves extremely useful for the decision maker in selecting the best choice, which for this decision environment is manufacturing strategy project 8. If for some reason management decides that this project cannot be implemented then they can go with the next best option, which is manufacturing strategy project 4. Thus, a portfolio decision (when a group of projects is to be selected) may provide different results that managers would be unhappy with if their preferences were not considered.

5. CONCLUSION

In this paper, we have provided a decision framework for evaluating alternative manufacturing strategy. Our methodology utilized a combination of Analytic Network Process (ANP) and Data Envelopment Analysis (DEA) models for this purpose. We have effectively demonstrated the use of these techniques in incorporating both manufacturing strategy information from qualitative data and hard numerical information from quantitative data into the decision making process. Qualitative, quantitative, manufacturing and strategic measures need to be considered in the evaluation of any manufacturing strategy. Manufacturing strategy selection, in practice for the manufacturing project to be successful, needs to consider the strategic objectives of the organization. These frameworks bring these issues together. The illustrative example showed the importance of integrating managerial preferences and judgments into decision models and their impact on the final selections made. The detailed networks, elements, and components were illustrative and may include fewer or additional clusters, factors and relationships. But, additional clusters and factors can greatly increase the effort and complexity of the model, lessening its practical utility. The Analytic Network Process (ANP) technique not only helps to quantify factors and incorporate manufacturing preference, but also helps for "think through" the decision. The network helps the decision process for manufacturing strategy, structuring their decision environment in a logical relationship. A major limitation in the proposed approach relates to the data used for the manufacturing measures. The final measures for the DEA/AR model had to be quantified for the model to work. There are DEA models that considered categorical and ordinal factors. Reformulating these models to incorporate manufacturing preferences is another research direction.

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