Operations strategy and flexibility: modeling with Bayesian classifiers

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Abstract

Purpose – Information analysis tools enhance the possibilities of firm competition in terms of knowledge management. However, the generalization of decision support systems (DSS) is still far away from everyday use by managers and academicians. This paper aims to present a framework of analysis based on Bayesian networks (BN) whose accuracy is measured in order to assess scientific evidence.

Design/methodology/approach – Different learning algorithms based on BN are applied to extract relevant information about the relationship between operations strategy and flexibility in a sample of engineering consulting firms. Feature selection algorithms automatically are able to improve the accuracy of these classifiers.

Findings – Results show that the behaviors of the firms can be reduced to different rules that help in the decision-making process about investments in technology and production resources.

Originality/value – Contrasting with methods from the classic statistics, Bayesian classifiers are able to model a variety of relationships between the variables affecting the dependent variable. Contrasting with other methods from the artificial intelligence field, such as neural networks or support vector machines, Bayesian classifiers are white-box models that can directly be interpreted. Together with feature selection techniques from the machine learning field, they are able to automatically learn a model that accurately fits the data.

Keywords Service operations, Bayesian statistical decision theory, Knowledge management

Paper type Research paper

Introduction

The use of information analysis tools for supporting business decisions is becoming a need for managers in the current complex and turbulent business environment (Barrientos and Vargas, 1998). The fast progression of technical advances drives industries towards competition on information in order to prevent and anticipate changes in customer needs, technology, new industrial trends and other competition parameters (Anderson and Lenz, 2001). However, improvements and generalization of use of decision support systems (DSS) have not achieved much progress. Actually, the evolution of business computing networking and client-server architectures are impelling the utilization of shared

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information in a decision support context (Burstein and the International Society for Decision Support Systems, 2001; Sounderpandian et al., 2005), but still much is to be done to enhance learning and knowledge improvement through management information systems. Moreover, the use of methods of formal reasoning has been scarcely applied to scientific evidence assessing, especially in the field of operations management (OM) (Lotfi and Pegels, 1996; Garbolino and Taroni, 2002). In fact, even though management information systems literature has broadly dealt with tools to assist in managerial decisions, the wide utility these systems generate for academicians research seems not to have still been discovered (Barthelemy et al., 2002).

Though, methods dealing with formal analysis are widely used to assess evidence in empirical studies. The statistical techniques of multivariate analysis are present in most OM studies research. However, the amount of dependencies that may exist among different aspects of the evidence is increasing the opportunities of improving accuracy in the results. Therefore, methods of formal reasoning have been proposed to assist researchers in analyzing all dependencies and relationships among variables (Garbolino and Taroni, 2002). In this context, Bayesian networks (BN) represent a general pattern of inference, which can be suited to particular studies. By disaggregating an inference problem into smaller “problem modules” which are solved separately, it is possible to obtain solutions for the larger problem (Pearl, 1988). Hence, problems occurring at the level of scientific evidence can be better understood and then, through the use of probability calculus and statistical techniques can be made to cohere with the entire evidential body (Neapolitan, 1990).

OM decisions are usually categorized into strategic and tactical (Schroeder, 2000). Tactical decisions tend to be structured under a formal framework of reasoning (Markland et al., 1998). Hence, optimization methods cover and solve most problems with high rates of accuracy. However, strategic decisions nature is unstructured and there is no a formal process of reasoning that suits all possible choices especially in situations of missing data (Brown and Kros, 2003). Moreover, dependency and influence among variables is not as clear as for tactical decisions. It is in this point where DSS play a fundamental role in order to increase knowledge of the interdependencies among strategic variables. Basically, a DSS can be defined as a computer system that deals with a problem where at least some stage is semi-structured or un-structured. Usually, and due to the ill-defined nature of information, DSS require relational database systems or the more recent data warehouses and flexible query languages. Knowledge management through model design demands the use of techniques from artificial intelligence and expert systems to provide smarter support not only for decision making but also to improve knowledge quality (Klein and Methlie, 1995). Thus, one of the main challenges is the embracement of a much more comprehensive view of OM strategic decisions-making DSS capable of handling less structured information and broader concerns than mathematical models (Mintzberg and Raisinghani, 1976). In the past, most of the research efforts in operations research focused on the development of new algorithms to solve problems faster. In fact, important advances have been achieved in different OM-related fields such as forecasting – see for instance Nikolopoulos and Assimakopoulos (2003). Now, DSS applications like BN can broad knowledge in OM decisions through new enhancement the researchers can benefit from. This new range of possibilities motivates research on applying new DSS-based methodologies to OM studies. The fast development of algorithms and increase on accuracy of BN
encourage academicians as well as practitioners to find new ways to incorporate these techniques in the decision-making process of the firms.

BN are widely accepted as an artificial intelligence tool for capturing uncertainty in problem solving (Nadkarni and Shenoy, 2001). They provide a valuable aid for representing relationships among variables in situations of uncertainty. They also help to clearly describe complex problems by generating information about their structure. Therefore, it is possible to calculate the effect of knowing the truth of one proposition or piece of evidence on the plausibility of others. BN are especially helpful as researchers often are unable to follow a logical framework in complex situations (Aitken and Gammerman, 1989). Bayesian inference supported by BN facilitates understanding of the system structure. Also, critical variables are identified while other influencing variables are outlined to be taken into account. Dynamic relationships are specified in probabilistic terms, which help to understand the real importance of mutual interconnectivity of variables along time. Actual applications show good results detecting malicious e-mails for protection purposes (Dong-Her et al., 2004) as well as market segmentation (Kuong-Wei and Kuo-Fang, 2002).

For quantitative information, it is possible to incorporate the user’s knowledge into the model on the basis of, for instance, information obtained from surveys or other sources. Therefore, models containing statistical relationships and elements belonging to the researcher’s knowledge can be created (Spiegelhalter et al., 1993). Causal maps have emerged as a knowledge representation tool that describes knowledge more descriptively than other models such as regression or structural equations (Fiol and Huff, 1992). Through causal maps, it is possible to provide a qualitative interpretation of the variables representing a decision problem. In addition, identifying the level of uncertainty is crucial in order to make inferences. Also, a dynamic approach helps to learn about causal relationships that represent complex and uncertain decisions (Heckerman, 1996). This is where BN help by suggesting a quantitative way to make inferences in causal maps. Hence, BN in which dependence relations are causal are also known as causal belief networks or causal probabilistic networks. Bayesian causal maps let us analyze the sensitivity of variables of interest by using evidence propagation algorithms (Nadkarni and Shenoy, 2001). However, relationships among variables in BN should not be interpreted in general as causal relationships, especially when there is not previous empirical evidence or expert opinion that could suggest such causality. Hence, the purpose of this research is to apply BN in a decision-making context through a database of strategic and flexibility variables regarding the engineering consulting sector. In this work, a BN is learned from a sample of engineering consulting firms in order to analyze relationships among different constructs. Therefore, after the process is finished, a close insight to the relationships among variables will be available as a base for future decision making.

Thus, the use of a machine-learning tool (MLT) based on BN is introduced to assess scientific evidence about OM decisions over a study made on engineering consulting firms. This paper is organized into the following sections. In the next section, we provide some BN background on how this tool can enhance scientific evidence and how they can be used to build classifiers in order to extract relevant information. Also, some algorithms for selecting features are shown in order to remove irrelevant attributes from a sample in a learning process. Secondly, the main elements and constructs regarding strategy and flexibility in the field of OM are described. Afterwards, empirical results obtained by using different algorithms are provided to build BN for
knowledge representation of relationships between different dimensions of operational flexibility and strategies in service management operations. Finally, the main conclusions and future research are discussed.

**Bayesian networks**
A BN consists of, firstly a directed acyclic graph (DAG) where each node represents a random variable and arcs represent probabilistic dependencies between these variables. This part of the network is called the structure, the model or the qualitative part of the BN, secondly a conditional probability distribution of the form \( P(x|\pi_x) \) for each node \( x \) given its parent set \( \pi_x \). This part of the BN is called the parameters or the quantitative part of the network.

The main independence assumption represented by a BN is the one called local Markov property: each node is independent of all its non-descendent nodes, given its parents. Thus, the joint probability distribution expressed by the BN can be obtained as the product of the conditional probability distributions:

\[
P(x_1, x_2, \ldots, x_n) = \prod_{i=1,\ldots,n} P(x_i|\pi_{x_i}).
\]

In order to build a model of a BN and/or its parameters, a Bayesian approach is frequently applied. This approach allows taking into account both the opinion of the researcher or expert and also the available data. The opinion of the expert is termed as prior knowledge. The graphical structure \( S \) of a BN considering only the expert opinion does not usually achieve a high degree of accuracy due to the large number of alternatives. Empirical data can be used to increase model accuracy. The process to define a BN partially or completely from data is called learning BN from data. When learning a BN two steps have to be performed. First, a model has to be inferred and second, the conditional probability distributions have to be obtained. Both steps will be followed when analyzing the interdependencies and relationships of the different OM decisions in this study.

**Bayesian classifiers**
A classifier is a function that assigns a class label to instances described by a set of attributes. When a BN is defined only to assign values for a discrete variable, the class, given a set of attribute values, this BN will work as a classifier. As an example, Bayesian classifiers are applied as part of a DSS in financial companies for decision-making processes related to credit card applications and/or loan approvals. Examples of attributes are the amount of money currently in a checking bank account vs salary assignment, credit records, seniority in the same employment, personal status or the loan purpose.

Other different approaches have been used to build classifiers from data. Thus, in the machine-learning field, classifiers have been defined by representing functions using decision trees, neural networks or, more recently, support vector machines (Vapnik, 1998). One of the most effective BN classifiers, in spite of its simplicity, is the one called naive Bayes (NB) classifier. The model of the BN used by this classifier makes a strong independence assumption: all the attributes \( x_1, x_2, \ldots, x_n \) are conditionally independent given the class \( y \) as shown in Figure 1(a). Figure 1(b) shows the structure of a NB classifier for the DSS about a credit authorization with four input variables.
The NB algorithm was used among other applications to learn a Bayesian classifier from a dataset with information about 690 credit card applications in an Australian bank, called *crx* (Blake et al., 1998). Each application contained 15 categorical and continuous attributes. The NB algorithm achieved 83 percent generalization accuracy, measured by using a five-fold cross-validation. This implies that an erroneous decision was made in 17 of 100 credit card applications. Accuracy increased up to 88 percent when only the most relevant input attributes were chosen by using a wrapper feature selection algorithm (John et al., 1994). Recently, more sophisticated models have been defined and tested in the machine learning literature. One of these models, called augmented naive (AN) BN (Friedman et al., 1997), allows edges among the attributes, thus reducing the strong assumptions existing in the NB classifier.

All AN structures reduce the strong independence assumption of the NB, so that a learning algorithm it is to be used to build the structure from data. Some algorithms to learn AN structures have been analyzed in AI literature in the last decade (Friedman et al., 1997). One of them is worth mentioning given its high-predictive performance and accurate results. It is called construct-TAN (cTAN) because it builds tree augmented naive (TAN) BN (Friedman et al., 1997). In a TAN structure (Figure 2) the class variable has no parents and each attribute has as parents the class variable and at most one more attribute. The cTAN algorithm takes into account the especial status of the class variable in order to improve the performance (Friedman et al., 1997).

A wider generalization of the NB algorithm allows building any kind of AN structures, i.e. each input attribute $x_i$ can have any number of parents considering that directed cycles are not allowed (Figure 3). This algorithm, called structured-AN (sAN)
(Hernández and Abad-Grau, 2001) was tested for several datasets at the UCI repository (Blake et al., 1998) achieving high levels of accuracy.

When the structure is too complex, a high risk of overfitting exists, i.e. conditional dependencies are estimated with a small number of instances and will become inaccurate estimators for the whole population. The algorithm sAN is based on the structural risk minimization (SRM) principle (Vapnik, 1995, 1998) to reduce the risk of overfitting. SRM principle defines a trade-off between the quality of the approximation of the given data and the complexity of the model. Several learning algorithms have also been defined to build classifiers with a structure different from AN, i.e. classifiers based on unrestricted or complex networks (Friedman et al., 1997; Aha and Ezawa, 1997; Sakellaropoulos and Nikiforidis, 2000). These algorithms have a higher time complexity. When compared with cTAN, generalization accuracy does not improve (Friedman et al., 1997).

Learning algorithms defined to construct Bayesian classifiers belong to the called sample paradigm (Dawid, 1986). Some relevant drawbacks of algorithms using this paradigm are:
lack of robustness for superfluous attributes; and
• low-generalization accuracy for small samples or a high dimensionality.

By ignoring this problem, the accuracy results of a Bayesian classifier in presence of short samples or a large number of input attributes can be severely affected. As a rule of thumb, a feature selection mechanism should always be used along with the learning process of the Bayesian classifier.

Feature selection
Test results accuracy for Bayesian classifiers is strongly increased when feature selection is performed. Depending on the direction of attributes selection, three types of algorithms can be considered (Caruana and Freitag, 1994): forward sequential selection, backward sequential elimination and bidirectional hillclimbing. Among them, the first one achieves the lowest computational time, considering that just a few amount of features are usually selected.

Extant literature has evaluated how the feature selection strategy interacts with the learning algorithm (Blum and Langley, 1997). Two main interaction methods have been defined (John et al., 1994): those that filter input attributes before using the learning algorithm and those that apply feature selection as a wrapper around the induction process. Usually the wrapper approach provides a higher accuracy than filtering methods that may have an entirely different inductive bias (Blum and Langley, 1997; John et al., 1994). However, wrapper approaches have a higher computational cost.

Elements of the study
In this study, a BN was defined to increase knowledge about the relationship between operations strategy and flexibility. Expert opinion obtained through questionnaires was the base of the research for evaluation of accuracy. A BN formal analysis has been performed based on a sample to make inferences. Thus, the learning process has involved a pure learning from data process in order to analyze how a set of variables influences the class. A feature selection method has also been utilized in order to increase the system accuracy by choosing a set of relevant attributes. A study using path analysis as multivariate statistical method was performed in Arias (2002). However, the Bayesian classifier learned by using a learning algorithm together with a feature selection enhances the quality of the knowledge extracted from the questionnaires. In this sense, the BN has shown the probabilistic relationships between those operation strategy variables with a relevant influence on flexibility.

Strategy in service operations management
Strategy in OM is one of the most studied constructs in the last decades (Waller, 1999). Literature on service OM has identified three basic operations strategies according to the firm’s focus of activities. Therefore, service industries can pursue process, service or customer-oriented operations strategies – see among others Johnston (1994), Haynes and Du Vall (1992), Bowen and Youngdahl (1998), Hart (1995), Desatnik (1994), Berry and Parasuraman (1997), Lush et al. (1996), Meredith et al. (1994), Tersine and Harvey (1998), Collier (1994, 1996) and Sampson (1996). Nine dimensions configure the basic service operations strategies (Arias, 2002). Table I shows the influence of each of these service strategy dimensions on the three basic service strategies. These
<table>
<thead>
<tr>
<th>Dim.</th>
<th>Process oriented</th>
<th>Customer oriented</th>
<th>Service oriented</th>
</tr>
</thead>
<tbody>
<tr>
<td>I</td>
<td>Process Layout. Service process activities are mainly sequential. Service location is usually not movable. Main process goal is space optimization. Workforce is highly specialized.</td>
<td>Product (service) layout. Service delivery tasks are neither sequential nor fixed located. Tasks allocation is flexible.</td>
<td>Layout is hybrid, although usually process oriented. Service delivery tasks tend to be sequential, though task variability leads to a significant degree of customization through changes in location. Operations are pull oriented. Process capacity tends to be low. Only small demands can be satisfied. Most process activities are customized, although customization range is small. There are many different ways to accomplish tasks. Pre-defined general procedures drive service delivery.</td>
</tr>
<tr>
<td>II</td>
<td>High investments in capacity satisfy large demands supported by strong marketing efforts. Process is push oriented.</td>
<td>Service-delivery process is Pull oriented. Customer satisfaction drives service-delivery process.</td>
<td></td>
</tr>
<tr>
<td>III</td>
<td>Most activities are standardized. There is one or few ways to achieve service delivery tasks. Task variability is to be minimized. Work procedures are pre-established.</td>
<td>Most service delivery activities are customized. There are few pre-established procedures to develop service delivery tasks.</td>
<td></td>
</tr>
<tr>
<td>IV</td>
<td>Range of different services offered is short and services are usually closely related.</td>
<td>Differentiation of the services provided is high. Every service delivered can be considered as unique.</td>
<td>There are few different offered services, being all of them closely related. Diversification is low.</td>
</tr>
<tr>
<td>V</td>
<td>New technologies investments are accomplished in order to reduce costs. Workforce tends to be replaced by technology.</td>
<td>Use and investment in new technologies has as the main goal to increase customer satisfaction.</td>
<td>Use and investment in new technologies tends to balance cost reduction and customization.</td>
</tr>
<tr>
<td>VI</td>
<td>Back and front office activities are physically separated in order to increase efficiency.</td>
<td>Back and front office activities are physically and integrated by sharing personnel. Customer gets on line information about service delivery.</td>
<td>Back and front office activities tend to be physically separated, although they share personnel. Such separation is usually due to space optimization.</td>
</tr>
<tr>
<td>VII</td>
<td>Workforce is highly specialized. Versatility is low. Every worker accomplishes one of few very specific tasks.</td>
<td>Personnel is not highly specialized but trained for versatility. Anybody must be able to develop any task totally or partially.</td>
<td>Personnel are very specialized. However, they are trained for versatility and fast adaptation to organizational and technology change.</td>
</tr>
<tr>
<td>VIII</td>
<td>Low customer contact. Customer participates in the service process only to reduce costs for the firm.</td>
<td>High degree of customer contact in order to customize service.</td>
<td>Degree of customer contact is high. Customer participation in the service-delivery process is high in order to customize service.</td>
</tr>
<tr>
<td>IX</td>
<td>Design and development of new services and processes is not strongly supported.</td>
<td>High intensity in design and development of new service. New services and processes are being developed continually.</td>
<td>Low intensity in design and development of new services and processes.</td>
</tr>
</tbody>
</table>

Source: Arias (2003)
dimensions configure the nine attributes analyzed in the study through BN. Such attributes are:

1. Type of operations layout. It directly influences the way operations are configured in the service-delivery process. A process layout tends to organize service delivery as a sequential activities process (Hart, 1996). On the opposite side, product layout does not imply task sequentiality. This leads to task development with no pre-established order (Johnston, 1994). Mixed layouts in which only a part of the service-delivery process is sequential while other parts are developed according to service specific characteristics have also been considered (Haynes and Du Vall, 1992).

2. PUSH/PULL orientation. PUSH/PULL orientation of the process determines the production philosophy of the service delivery. PULL oriented service firms initially consider customer needs when developing service activities. Activities do not end until the service firm has satisfied perceived customer expectations (Bowen and Youngdahl, 1998). PUSH oriented service firms undertake important investments in production capacity in order to satisfy demand. Demand is fostered through big marketing efforts (Hart, 1995; Tersine and Harvey, 1998). Also, mixed PUSH/PULL configurations are considered.

3. Degree of service standardization. It refers to the extent to which task procedures are pre-established. Therefore, it also influences employees’ empowerment (Bowen and Schneider, 1995; Mills and Morris, 1992). Standardization tries to minimize variability in the service-delivery process, so procedures of developing each task are limited (Hart, 1996).

4. The number of different services. It measures the degree of diversification of the firm according to the final products/services delivered (Desatnik, 1994). This dimension shows how the firm is oriented towards many or few customer segments (Lewis and Klein, 1984). It also regards how related the final products/services are, so a firm offering two products/services lines with few similarities between them is considered to detain a higher degree of product/service amplitude than a firm offering many related products/services lines.

5. Use of information technologies (IT). This dimension is considered according to two parameters. On one side, IT can be used in order to reduce costs through, for instance, substitution of workforce by technologies (Berry, 1995). On the other side, IT investments can be made for final service improvement, like, for instance, through simulation technologies to verify service quality and reliability (Siehl, 1992; Quinn and Paquette, 1990). In addition, causal ambiguity around technological competencies can help firms to achieve superior performance (González-Alvarez and Nieto-Antolín, 2005).

6. The relationship between front and back office activities. It refers to physical location as well as to workforce information exchange. Such relationship directly affects customer perception on service delivery. When both activities are physically separated, customer effort to obtain information about back office activities is higher and will be moderated by the mechanisms of information exchange between both front and back office activities (Price et al., 1995; Lush et al., 1996). However, physical closeness of both activities increases information effectiveness and reliability for the customer.
(7) **Degree of workforce specialization.** It intends to determine personnel versatility when accomplishing various and different activities. Hence, the staff can be prepared either to undertake one or few specific tasks or else, to carry out any activity total or partially (George, 1990; Meredith *et al.*, 1994; Tersine and Harvey, 1998). A more versatile workforce responds more quickly and efficiently to environmental changes while highly specialized personnel tend to be more rigid (Ashford and Humphrey, 1993; Schneideran and Bowen, 1993; Bowen and Lawler, 1995). This fact is especially relevant for those service firms that have IT with fast degree of obsolescence as basis of their activity.

(8) **Degree of customer contact and participation.** It relates to the level of interaction between customer and service-delivery process. Such interaction can be utilized either to transfer some activities to customers in order to reduce process costs or to customize service delivery (Bolton and Drew, 1991; Cadotte and Turgeon, 1988). In the first case, the customer acts as staff by developing tasks of the service-delivery process (Lampel and Mintzberg, 1996). In the second case, the customer exchanges information with the performers of the service delivery activities, but such activities are developed in the firm (Collier, 1994, 1996; Gouillart and Sturdivant, 1994). In both cases customer act as a quality controller by assuring that his/her expectations fits his/her perceptions at least for those tasks he/she performs.

(9) **Finally, intensity of design and development of new services.** It refers to whether or not the firm sets new service delivery procedures through new tasks organizations and investments in specific resources. Therefore, this dimension assesses the firm willingness to innovate in new processes and services (Arias *et al.*, 2001; Bowen and Youngdahl, 1998; Bowen and Schneider, 1995).

**Flexibility**

One of the key challenges to achieve a flexible operations system emerges when focusing and managing the different dimensions of flexibility (Gerwin, 1993). This is mainly due to the fact that flexibility is not accumulative; so more flexibility in different parts of the system does not imply a more flexible operations system. Changes in flexibility are of strategic nature, so they should not only involve process engineers but also production and even business managers (Chambers, 1992). Operations strategy determines the level of uncertainty to be supported by the service delivery system by adapting the different flexibility dimensions to environmental changes (Gerwin, 1993; Chambers, 1992). OM literature has focused on identifying different dimensions and types of flexibility (Browne *et al.*, 1984; Chatterjee *et al.*, 1984; Carter, 1986; Gerwin, 1987; Son and Park, 1987; Brill and Mandelbaum, 1989; Ahn and Hyun, 1990; Gupta and Goyal, 1992; Gupta and Somers, 1992) (Table II).

In service industries, customer interaction and customization imply a high degree of flexibility. Nowadays, customers are more demanding for integral services provided by the same firm (Vandermerwe, 1992). This fact will entail a new and different conception of service flexibility. However, electronic data interchange (EDI) and information technologies (IT) provide of new market opportunities for service firm without high-flexibility investment efforts (Chang *et al.*, 2005; Chiu and Chen, 2005). Consequently, reengineering processes are easier to accomplish in service delivery systems than in manufacturing systems (Davis and Vokurka, 2005). Also, service firms
<table>
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<th>Flexibility dimensions</th>
<th>Definition</th>
<th>Measures</th>
<th>References</th>
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<tr>
<td>I. Expansion flexibility</td>
<td>Ease with which capacity can be added when needed</td>
<td>(1) Overall cost and time needed to add capacity (2) Upper limit on the amount of capacity expansion</td>
<td>Carter (1986) and Browne et al. (1984)</td>
</tr>
<tr>
<td>II. Flexibility on</td>
<td>Capability to distribute information through the service-delivery process</td>
<td>Ratio of the number of information resources available in a system to the number of possible paths</td>
<td>Chatterjee et al. (1984) and Newman et al. (1993)</td>
</tr>
<tr>
<td>distribution of information</td>
<td></td>
<td>(1) Average number of ways in which a service can be delivered (2) Routing entropy (3) Decrease percentage in the throughput caused by machine breakdowns or personnel errors (4) Cost of services lost due to rescheduling an urgent job</td>
<td>Chung and Chen (1990), Jaikumar (1986) and Browne et al. (1984)</td>
</tr>
<tr>
<td>III. Routing flexibility</td>
<td>Capability to use alternative processing routes to deliver a service</td>
<td>(1) Number of different operations performed by machines and workforce weighted by the importance of tasks (2) Cost of switching from one operation to another (3) Extent of variation in the inputs that the machine or worker can handle</td>
<td>Brill and Mandelbaum (1989), Sethi and Sethi (1990) and Gerwin (1987)</td>
</tr>
<tr>
<td>IV. Equipment and</td>
<td>Capability of machines and personnel to perform different operations</td>
<td>(1) Ratio of average volume fluctuation to total capacity (2) Stability of service costs over widely varying levels of servuction volume (3) Smallest volumes for profitable operation of the system</td>
<td>Gerwin (1987), Falkner (1986) and Browne et al. (1984)</td>
</tr>
<tr>
<td>personnel flexibility</td>
<td></td>
<td>(1) Ratio of total output to set-up costs (2) Number of services delivered by year (3) Time or cost to change from one service to another (4) Option pricing approach</td>
<td>Son and Park (1987), Jaikumar (1986) and Browne et al. (1984)</td>
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<tr>
<td>V. Market flexibility</td>
<td>Capability to operate at different levels of output</td>
<td></td>
<td></td>
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<tr>
<td>VI. Services and servuction</td>
<td>Capability of the system to add or substitute services without major efforts</td>
<td>(1) Ratio of total output to set-up costs (2) Number of services delivered by year (3) Time or cost to change from one service to another (4) Option pricing approach</td>
<td>Son and Park (1987), Jaikumar (1986) and Browne et al. (1984)</td>
</tr>
<tr>
<td>flexibility</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>VII. Process, programming and</td>
<td>Capability to produce different service types without major effort, capability of service parts to be delivered in different ways, capability of a system to operate unattended for long periods</td>
<td>(1) Number of different parts that can be produced (2) Changeover costs between different known jobs within the current production plan (3) Expected value of a portfolio of product for a given set of contingencies</td>
<td>Browne et al. (1984), Gerwin (1987) and Jaikumar (1986)</td>
</tr>
<tr>
<td>volume flexibility</td>
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**Source:** Adapted from Ramasesh and Jayakumar (1991)
are able to design delivery systems in which customers are actively involved, becoming self-service delivery systems (Ruiz et al., 2005). This makes flexibility simpler and easier to implement considering that the customer develops certain activities of the service delivery system, especially when compared to the high costs of workers training for manufacturing firms (Palanisamy, 2005). From the above discussion, it can be inferred that service operations strategy and service delivery flexibility are deeply interrelated. However, the relationships among the different dimensions configuring both constructs and the strength and magnitude of such relationships are still to be determined. Once the different constructs and dimensions have been defined we intend to increase knowledge about the relationship between OM and flexibility through BN analysis.

**Empirical study**

*Sample and the sampling procedure*

Data were obtained from a sample of a panel of experts from engineering consulting firms in Spain. The dimensions of operations strategy are of particular importance in this service sector. Three firm types (civil, industrial and environmental) were considered covering most activities of engineering consulting firms. Data were collected from experts predominantly via e-mail and personal interviews to the operations managers/executives or equivalent having a high level of responsibility in their companies. The Association of Spanish Engineering Consulting Firms (Tecniberia) provided information about the sector. Initially, and in order to attract the maximum number of participating firms, an e-mail was sent to all firms registered in Tecniberia soliciting their participation while stressing the importance of the study. The researchers considered a total of 129 firms with a turnover higher than €150.000. As a second step, a copy of the questionnaire was sent to all of them previously to personal interviews to those managers who opted for it. Finally, usable data were collected from a total of 71 firms (55 percent of the total population). The questionnaire original language was Spanish (see Appendix). Table III shows a description of the sample according to the five turnover categories.

Comparing the sample distribution with the sector as a whole, no significant discrepancies were observed. Most of the firms’ turnover ranged from €300,000 to €3,000,000 (60 percent approx. of the total sample). On the other hand, civil engineering firms represented the higher percentage of the sample (49 percent) compared to 17 percent of industrial engineering and 34 percent of environmental engineering. Table IV shows the turnover distribution of the firms according to Ministerio de Fomento (1998).

<table>
<thead>
<tr>
<th>Cat</th>
<th>Turnover (€)</th>
<th>Firms</th>
<th>Civil Percentage</th>
<th>Group of activity</th>
<th>Firms</th>
<th>Industrial Percentage</th>
<th>Environmental Firms</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>&lt;300,000</td>
<td>7</td>
<td>20.0</td>
<td></td>
<td>3</td>
<td>25.0</td>
<td></td>
<td>7</td>
</tr>
<tr>
<td>2</td>
<td>300,000-600,000</td>
<td>11</td>
<td>31.4</td>
<td></td>
<td>3</td>
<td>25.0</td>
<td></td>
<td>7</td>
</tr>
<tr>
<td>3</td>
<td>600,000-3,000,000</td>
<td>11</td>
<td>31.4</td>
<td></td>
<td>4</td>
<td>33.3</td>
<td></td>
<td>8</td>
</tr>
<tr>
<td>4</td>
<td>3,000,001-6,000,000</td>
<td>3</td>
<td>8.6</td>
<td></td>
<td>0</td>
<td>0.0</td>
<td></td>
<td>2</td>
</tr>
<tr>
<td>5</td>
<td>6,000,000 and more</td>
<td>3</td>
<td>8.6</td>
<td></td>
<td>2</td>
<td>16.7</td>
<td></td>
<td>0</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>35</td>
<td>100.0</td>
<td></td>
<td>12</td>
<td>100.0</td>
<td></td>
<td>24</td>
</tr>
</tbody>
</table>

*Source:* Own processing
Most questions related to operations strategy were based on a five-point Likert scale while some others were open questions. Every one of the nine dimensions of operations strategy was clearly represented in differentiated blocks in the questionnaire. Control questions were included in order to verify internal consistency of the questionnaire. For every dimension, a set of items was included in the questionnaire. For every item a Likert scale ranging from one (completely agree) to five (completely disagree) was used to measure agreement of the operations managers/executives with such items.

**Learning algorithms**
Six different algorithms were applied to infer Bayesian classifiers from data. Two of them, called NB and smoothed NB (sNB), respectively, build naive Bayesian classifiers. The next two, called construct-TAN (cTAN) and smoothed cTAN (scTAN), build TAN classifiers. The remaining two build any AN classifier, and they are called structured-AN (sAN) and smoothed sAN (ssAN).

While the unsmoothed algorithms do not consider a prior distribution, in the smoothed algorithms a prior distribution considering a Bayesian approach to infer the conditional distributions in the classifiers was used. Even though they are very simple structures, as those in the NB classifier, they performed well with the unsmoothed version. In addition, a significant improvement by using the Bayesian approach with more complex structures was reported (Friedman et al., 1997; Abad-Grau and Hernández, 2001).

These learning algorithms were used to infer seven different classifiers, one for each flexibility dimension referred above. The software was implemented in C++ as a part of the MLT (Abad-Grau, 2001). Each sample used was composed of 72 instances, each one for a different service industry. Each instance had 84 input attributes and as class attribute the flexibility dimension. The class attribute in the seven samples had five different categories: 1, 2, 3, 4, 5. Input attributes were the same in all the samples. They came from the nine basic dimensions defining the service operation strategies. Each dimension was composed of 12, 7, 11, 6, 8, 4, 5 and 4 categorical attributes, respectively. Values for each attribute were included in the set 1, 2, 3, 4, 5.

Learning-from-data algorithms need a dataset to infer the classifier. This dataset is called the training set in the machine learning community. In order to measure the generalization accuracy of the classifier, i.e. how well the classifier will perform with a new instance, a not previously used dataset should be chosen. This dataset is called the test dataset. Usually only one dataset is provided. In order to reduce the variance, instead of split it into a training dataset and a test dataset, other solutions such as cross validation are frequently applied. In cross validation, the original dataset is divided in $f$ folds. The learning algorithm is used $f$ times. Each time $t, t \in \{1, 2, \ldots, f\}$ the algorithm is run, the test dataset is composed of all the instances at fold $t$ and a different classifier can be inferred by using as a training dataset all the instances in the remaining $f-1$ folds. Test accuracy is computed for each classifier.

<table>
<thead>
<tr>
<th>Turnover (€)</th>
<th>&lt;300,000</th>
<th>300,000-600,000</th>
<th>600,001-3,000,000</th>
<th>3,000,001-6,000,000</th>
<th>&gt;6,000,000</th>
</tr>
</thead>
<tbody>
<tr>
<td>Percentage firms</td>
<td>27.3</td>
<td>32.3</td>
<td>27.2</td>
<td>6</td>
<td>7.2</td>
</tr>
</tbody>
</table>

*Source: Ministerio de Fomento (1998) (Spanish Ministry of Industry)*
The generalization accuracy reported is the averaged test accuracy for the $f$ folds used. When the number of folds $f$ equals the number of instance in the dataset, the evaluation method is called leave one out cross validation (LOOCV) (John et al., 1994) as only one instance makes up the test set in each algorithm execution.

In this study, five-fold cross validation was applied. In Table V test accuracy results are shown for these six learning algorithms and for the seven datasets. As it can be observed, smoothed algorithms performed better than the unsmoothed ones. Also, those allowing more complex structures, sAN and ssAN achieved higher-accuracy levels. The SRM inductive principle has always been used to control the overfitting risk derived from very complex structures. In general, predictive or generalization capacity (the averaged test accuracy) was very low for all algorithms used when all input attributes were considered.

In Table VI test accuracy results are shown for these five learning algorithms using a wrapper and forward sequential algorithm for feature selection. Several results reported in this table need to be highlighted. First, the test accuracy was highly increased, nearly doubled. Four of six algorithms showed a test accuracy over 90 percent, which implies that there were non-relevant attributes disturbing the classifier accuracy in all the samples. Selected attributes for each dataset are reported in Table VII. Moreover, the number of relevant features needed to infer the value of the flexibility dimension dramatically decreased in the seven samples. In addition, the smoothed approach of the more complex structures (compared to NB) were not needed once a feature selection algorithm was able to choose a set of relevant input attributes accurately. Best results were achieved by the NB classifier, even with the strong

<table>
<thead>
<tr>
<th>Learning algorithm</th>
<th>FBI</th>
<th>FBIi</th>
<th>FBIii</th>
<th>FBIiv</th>
<th>FIV</th>
<th>FVI</th>
<th>FVII</th>
<th>Average</th>
</tr>
</thead>
<tbody>
<tr>
<td>NB</td>
<td>45.0704</td>
<td>33.8028</td>
<td>67.6056</td>
<td>53.5211</td>
<td>35.2113</td>
<td>43.6620</td>
<td>53.5211</td>
<td>47.4849</td>
</tr>
<tr>
<td>sNB</td>
<td>42.2535</td>
<td>38.0282</td>
<td>64.7887</td>
<td>45.0704</td>
<td>47.8873</td>
<td>45.0704</td>
<td>61.9718</td>
<td>49.2958</td>
</tr>
<tr>
<td>cTAN</td>
<td>45.0704</td>
<td>33.8028</td>
<td>67.6056</td>
<td>53.5211</td>
<td>35.2113</td>
<td>43.6620</td>
<td>53.5211</td>
<td>47.4849</td>
</tr>
<tr>
<td>scTAN</td>
<td>42.2535</td>
<td>38.0282</td>
<td>64.7887</td>
<td>45.0704</td>
<td>47.8873</td>
<td>45.0704</td>
<td>61.9718</td>
<td>49.2958</td>
</tr>
<tr>
<td>sAN</td>
<td>46.4789</td>
<td>28.1690</td>
<td>67.6056</td>
<td>49.2958</td>
<td>35.2113</td>
<td>36.6197</td>
<td>54.9296</td>
<td>45.4728</td>
</tr>
<tr>
<td>ssAN</td>
<td>45.0704</td>
<td>36.6197</td>
<td>67.6056</td>
<td>49.2958</td>
<td>43.6620</td>
<td>43.6620</td>
<td>60.5634</td>
<td>49.4970</td>
</tr>
</tbody>
</table>

**Note:** Each sample contains for each firm its value for the corresponding flexibility dimension (the class attribute) and as input attributes, information about its decision in different operation strategy

**Source:** Own processing

<table>
<thead>
<tr>
<th>Learning algorithm</th>
<th>FBI</th>
<th>FBIi</th>
<th>FBIii</th>
<th>FBIiv</th>
<th>FIV</th>
<th>FVI</th>
<th>FVII</th>
<th>Average</th>
</tr>
</thead>
<tbody>
<tr>
<td>NB</td>
<td>95.7747</td>
<td>87.3239</td>
<td>94.3662</td>
<td>92.9578</td>
<td>94.3662</td>
<td>95.7747</td>
<td>88.7324</td>
<td>92.7565</td>
</tr>
<tr>
<td>sNB</td>
<td>95.7747</td>
<td>87.3239</td>
<td>92.9578</td>
<td>92.9578</td>
<td>92.9578</td>
<td>92.9578</td>
<td>92.9578</td>
<td>90.1409</td>
</tr>
<tr>
<td>cTAN</td>
<td>95.7747</td>
<td>87.3239</td>
<td>92.9578</td>
<td>92.9578</td>
<td>92.9578</td>
<td>92.9578</td>
<td>92.9578</td>
<td>90.1409</td>
</tr>
<tr>
<td>scTAN</td>
<td>95.7747</td>
<td>87.3239</td>
<td>92.9578</td>
<td>92.9578</td>
<td>92.9578</td>
<td>92.9578</td>
<td>92.9578</td>
<td>90.1409</td>
</tr>
<tr>
<td>sAN</td>
<td>95.7747</td>
<td>81.6901</td>
<td>91.5493</td>
<td>90.1409</td>
<td>83.0986</td>
<td>84.5070</td>
<td>78.8732</td>
<td>86.5191</td>
</tr>
<tr>
<td>ssAN</td>
<td>95.7747</td>
<td>80.2817</td>
<td>90.1409</td>
<td>90.1409</td>
<td>83.0986</td>
<td>84.5070</td>
<td>78.8732</td>
<td>86.1167</td>
</tr>
</tbody>
</table>

**Table V.** Test accuracy using different learning algorithms to infer Bayesian classifiers

**Table VI.** Test accuracy choosing a set of relevant features by using a forward-selection and wrapper mechanism

**Source:** Own processing
Table VII.
Selected set of input attributes by using the wrapper method upon the NB algorithm for each test set in the five-fold cross validation.

<table>
<thead>
<tr>
<th>Fold number</th>
<th>FBI</th>
<th>FBII</th>
<th>FBIII</th>
<th>FBIV</th>
<th>FBV</th>
<th>FBVI</th>
<th>FBVII</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>AIII9</td>
<td>AVI3</td>
<td>AVI4</td>
<td>AII2</td>
<td>Avi4</td>
<td>AII7</td>
<td>AIII4</td>
</tr>
<tr>
<td>2</td>
<td>A11</td>
<td>AIII3</td>
<td>AI12</td>
<td>AVI4</td>
<td>AI3</td>
<td>AII7</td>
<td>AVIII5</td>
</tr>
<tr>
<td>3</td>
<td>A14</td>
<td>AI16</td>
<td>AVII2</td>
<td>AII2</td>
<td>AVI2</td>
<td>AVIII3</td>
<td>AVIII4</td>
</tr>
<tr>
<td>4</td>
<td>A14</td>
<td>AVI3</td>
<td>AVII1</td>
<td>AI12</td>
<td>AVI1</td>
<td>AVIII3</td>
<td>AVIII5</td>
</tr>
<tr>
<td>5</td>
<td>A15</td>
<td>AII6</td>
<td>AVI3</td>
<td>AII4</td>
<td>AIII3</td>
<td>AI17</td>
<td>AVIII4</td>
</tr>
</tbody>
</table>

**Source:** Own processing
assumption of conditional independence among input variables given the class. It has to be noted that all the learning algorithms achieve the same test accuracy for flexibility dimension FBI. The explanation is straightforward: only one input variable was selected by the feature selection algorithm (Table VII) so that all the learning algorithms were equivalent. Thus, all of them used a very simple structure with only one input variable to which the class variable (FBI) points out.

**Discussion**

Algorithms based on the sample paradigm, such as those building Bayesian classifiers, obtained a lower accuracy with superfluous attributes and/or very small samples. Results obtained by NB algorithm in the seven datasets (Table VI) confirmed those reported in machine learning literature supporting the importance of this algorithm because of its simplicity, low-computational cost and high-generalization accuracy when only relevant attributes are used (Domingos and Pazzani, 1996).

In general, feature selection allows extracting relevant information from samples. Thus, simple Bayesian classifiers inferred by learning algorithms used together with feature selection algorithms can be used as knowledge extractors or data mining tools. Table VII shows the items related with strategy design that were chosen as relevant for each flexibility dimension. Each row in the table corresponds to a subsample in the five-fold cross validation method used to assess accuracy. If the same input attribute was selected in more than one subsample, the knowledge about its relevancy on the corresponding flexibility dimension was extracted. Therefore, the knowledge shown in Table VII according to items and dimensions used in Arias (2002) can be summarized as:

- AI4 (fixed layout) directly and strongly influences FBI (expansion flexibility).
- AVI3 (back and front office activities separation) directly and strongly influences FBII (flexibility on distribution of information).
- AVII2 (workforce versatility) directly and strongly influences FBIII (routes flexibility).
- AIII4 (low empowerment and service standardization) directly and strongly influences FBIV (flexibility on personnel and equipments).
- AVIII3 (customer training) directly and strongly influences FBV (market flexibility).
- AVIII4 (customer knowledge of price decrease when participation), AVIII5 (service customization) directly and strongly influence FBVI (service and servuction flexibility).
- AI3 (optimization of space) directly and strongly influences FBVII (flexibility of processing, programming and volume)

The first rule establishes the relationship between the use of a fixed layout and expansion flexibility. So, fixed layouts emphasize standardization in order to expand the servuction units to develop services which can be perceived as different even with small changes in design. The second rule points out that when back and front office activities are separated, flexibility in distribution of information increases. Structured, quantitative and specific information is easier to distribute as it is easier to codify.
The third rule indicates that versatile personnel increases routes flexibility as determined stages of services delivered can be performed by different staff. This also helps to decrease possible bottlenecks. The fourth shows that when services are standardized, they can be delivered through different equipments and servuction units. So, the firm is more flexible when some equipment and servuction units fail. The fifth rule shows that when customers participate and the firm helps them to design their own service, market flexibility is increased. Under these conditions, the firm can serve a wider target of customers, especially when they are aware of cost reduction (and also for price) through such participation. The sixth rule is closely related to the last one. It indicates that customer awareness of the consequences of his/her participation drives to higher flexibility on services delivery and servuction. Therefore, the capacities and resources of the firm are at the customers use for customization. Finally, the seventh rule pointed out how new services development needs more flexibility in process, programming and volume, especially when optimizing the physical space devoted to operations and servuction activity.

Conclusions

An application of the use of BN to support business decisions making to summarize information in some basic behavior rules has been analyzed in this paper. Basically, this tool can help practitioners and academicians to predict future adaptations to environmental changes. In this case, managers acquire knowledge about which operations strategy items directly influence determined flexibility dimensions. Academicians can determine which strategic variables support the different types of flexibility in services. Hence, BN become a powerful tool to help in technology and process resources investments in order to manage system flexibility accurately.

The main contribution of this research is based on the knowledge extracted from the data through BN. This knowledge can increase manager’s expertise when making decisions about strategy design and flexibility investments. Therefore, managers get to know which operations strategy dimensions influence the different types of flexibility. This knowledge, summarized in seven rules, supports the evidence from previous studies about the relationships between operations strategy and flexibility (see among others Arias (2003) for services or those previous of Ahn and Hyun (1990) and Newman et al. (1993) for manufacturing which served as a general framework for services). The managerial implications derived from the application of BN to the relationship between operations strategy and flexibility are three-fold. Strategic decisions regarding workforce and production technology have a direct influence on those flexibility dimensions related to internal aspects of industrial organization (distribution of information, routes, equipment . . .). On the other hand, those strategic decisions regarding customer approach and degree of customization affect external flexibility dimensions (market, services . . .). Finally, the strategic decisions focused on layout and optimizations of space impinge on how the servuction process adapt to changes in the environment (expansion, processing, programming and volume). Hence, small engineering consulting firms which intend to grow in the market tend to be more flexible at initial stages in order to attract a wider target of customers. Usually, workforce is very versatile, engineering projects are developed with a high degree of customization and space is optimized as it uses to be scarce in this small firms. Once the firms grow up to an intermediate stage, they need to balance the increase in the
number of customers and services to be delivered with their organizational structure. Generally, the workforce need to be more specialized, standardization emerges as the main servuction philosophy and layout is fixed to support the new structure. This medium size firms tend to decrease their flexibility standards to satisfy higher demands in a more standardized way. Finally, big size engineering firms can afford investments in resources and capabilities to increase flexibility in those areas that attract high-value customers and innovate in new markets. Consequently, managers can adapt the firm decision-making process according to the firm stage through the knowledge obtained with BN applications.

This research intended to be the first step of a series of research lines whose main goal is to generalize the use of DSS in the decisional business environment. Our future research lines involve the inclusion of more relevant variables in order to improve and create DSS for different sectors and environments. The development of friendly interfaces for knowledge acquirement is another part of the DSS which needs faster improvements. The quality of the information is basic to increase DSS reliability. Managers should easily introduce and extract new knowledge to and from the tools on a user-friendly basis. Finally, knowledge spread systems need to be adapted to particular needs of different departments and management areas in order to increase efficiency in decision making in every decisional point of the organization.

References


Appendix. Questionnaire
Set of items used to measure operations strategy dimensions for service management. Likert scale from one to five according to the degree of implementation:

Block A.I. Layout
Aspects of a fixed layout:
1. Service delivery activities are performed in a pre-established and fixed place.
2. Production resources are sequentially located.
3. Resources for service delivery are located in order to optimize space and maximize efficiency.
4. Downstream tasks are never performed until upstream tasks are over.
5. Every worker is assigned to an exclusive task.
6. System efficiency goals are have priority when designing service-delivery process.
Aspects of a movable layout:
7. Service delivery activities are performed where it is more convenient for the customer.
8. Production resources can move to those places where service is delivered.
9. Resources for service delivery are located in order to optimize customer satisfaction and final service delivery.
10. Workers assignment is made on a rotation basis.
11. Workers perform different tasks in the same shift.
12. Customer satisfaction goals are have priority when designing service-delivery process.

Block A.II. PUSH/PULL orientation
PUSH orientation.
13. Important marketing efforts are made in order to attract new customers.
14. A crucial marketing goal is that customer is delivered as much services as possible.
15. Production output is always maximized.
PULL orientation.
16. Important service delivery efforts for improvement are made in order to increase customers' satisfaction.
17. A crucial marketing goal is that customer is satisfied.
18. Customer satisfaction is more important than output optimization.

Block A.III. Level of standardization
19. Service delivery system is designed so there is one or a few ways to perform every task.
20. Variability is continually decreased along the service-delivery process.
21. Most work procedures are pre-established and cannot be modified.
22. Empowerment degree is very low.
23. All incidents not prevented in the work procedures must be communicated to a superior for resolution.
24. There is a procedures book, which is known by all workers.
25. Most service delivery activities are oriented towards service customization.
Block A.IV. Different services offered
(26) The firm offers a wide range of different services.
(27) All offered services are customized.
(28) New services are continually offered to customers.
(29) The firm delivers one of few very specialized services.
(30) Services are delivered to satisfy one or few small customer segments.

Block A.V. Use of ITs
(31) Acquisition of IT is oriented towards costs reduction.
(32) Workforce is replaced by new technologies when possible.
(33) Customers can send or receive information about service delivery through IT such as internet, EDI, WAP, ...
(34) Acquisition of IT is oriented towards customer satisfaction.
(35) Decisions about IT adoption are done on the basis of tasks improvements from the worker point of view.
(36) Decisions about IT adoption are done on the basis of service customization.

Block A.VI. Back and front office activities
(37) Front office activities are physically separated and differentiated from the back office activities.
(38) The customers cannot access those service activities in which they are not required.
(39) Personnel of front office activities works exclusively there and never in back office activities.

Block A.VII. Human resources
(40) Personnel are highly specialized.
(41) Personnel is able to perform various and different tasks.
(42) Job rotation is commonly used.
(43) More than half of our personnel are university graduates.
(44) Training is given a crucial importance in the firms budgets.

Block A.VIII. Customer participation
(45) Service-delivery process is designed so customer performs by him/herself those activities he/she is qualified for.
(46) Customer performs part of the service delivery activities in order to reduce costs.
(47) Customer is informed in detail about all previous activities he/she has to perform before service delivery.
(48) Customer knows about cost reductions due to his/her participation in the service-delivery process.
(49) Customer participates in the service-delivery process in order to customize service.

Block A.IX. Design and development of new products
(50) New procedures for service delivery are continually developed.
(51) New services are continually developed.
(52) Customer opinions are indeed considered when designing new services.
(53) There is an exclusive team for service design and development.

<table>
<thead>
<tr>
<th>Flexibility type</th>
<th>Measures (rate according to the level of importance in the firm from one [very low] to five [very high] in a Likert scale)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Expansion flexibility</td>
<td>Overall cost and time needed to add capacity</td>
</tr>
<tr>
<td></td>
<td>Upper limit on the amount of capacity expansion</td>
</tr>
<tr>
<td>Distribution of information flexibility</td>
<td>Ratio of the number of information paths available in a system to the number of possible paths</td>
</tr>
<tr>
<td></td>
<td>Increase in the performance of service delivery through the use of IT</td>
</tr>
<tr>
<td>Routing flexibility</td>
<td>Average number of ways in which a service can be delivered</td>
</tr>
<tr>
<td></td>
<td>Routing entropy</td>
</tr>
<tr>
<td></td>
<td>Decrease percentage in the throughput caused by breakdowns</td>
</tr>
<tr>
<td></td>
<td>Cost of production lost due to rescheduling an urgent job</td>
</tr>
<tr>
<td>Labor and equipment flexibility</td>
<td>Number of different operations performed by machines and personnel weighted by the importance of tasks</td>
</tr>
<tr>
<td></td>
<td>Cost of switching from one operation to another</td>
</tr>
<tr>
<td></td>
<td>Extent of variation in the inputs that machines or workforce can handle</td>
</tr>
<tr>
<td>Market flexibility</td>
<td>Cost of orders inattention</td>
</tr>
<tr>
<td></td>
<td>Cost of order delays</td>
</tr>
<tr>
<td>Services and servuction flexibility</td>
<td>Ratio of total output to set-up costs</td>
</tr>
<tr>
<td></td>
<td>Number of services delivered by year</td>
</tr>
<tr>
<td></td>
<td>Time or cost to change from one service to another</td>
</tr>
<tr>
<td>Process, programming and volume flexibility</td>
<td>Option pricing approach</td>
</tr>
<tr>
<td></td>
<td>Expected percentage uptime during second and third shifts</td>
</tr>
<tr>
<td></td>
<td>Number of different parts that can be produced</td>
</tr>
<tr>
<td></td>
<td>Changeover costs between different known jobs within the current production plan</td>
</tr>
<tr>
<td></td>
<td>Expected value of a portfolio of product for a given set of contingencies</td>
</tr>
<tr>
<td></td>
<td>Ratio of average volume fluctuation to total capacity</td>
</tr>
<tr>
<td></td>
<td>Stability of manufacturing costs over widely varying levels of production volume</td>
</tr>
<tr>
<td></td>
<td>Smallest volumes for profitable operation of the system</td>
</tr>
</tbody>
</table>

Table A1.

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