Productivity Evaluation: How Can Expert Systems Technology Help?

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Abstract

Productivity management is essential for long-term survival of the businesses. There are, however, serious obstacles to successful productivity management because many managers do not have the skills or time to analyze productivity and take necessary corrective actions in a timely fashion. Expert systems can come to the rescue because of their strengths in symbolic processing.

This paper presents successful expert systems and identifies the problems they solve. Then, it examines each stage of the productivity management process and discusses the appropriateness of expert systems applications for each stage. Examples of existing prototypes supplement the discussion.

1. Introduction

Productivity and profit margins remain the most important performance indicators for CEOs in their strategic decision-making, according to *Industry Week's* 27th annual survey of CEOs in 1998 [1]. Productivity is the relationship of the quantity of output produced by a system over a period of time to the quantity of resources consumed to produce that output over the same period of time. Productivity management within a firm should be an important managerial function if that firm is to remain competitive, but there are serious obstacles to productivity improvement. A survey by the Institute of Industrial Engineers asked practicing industrial engineers, who play a pivotal role in increasing productivity within their firms to cite the major obstacles to productivity. The top three responses were [2]:

1. Failure of management to apply proper measurement programs to evaluate productivity improvement.
2. Failure of management to understand how productivity can be improved.
3. Failure of management to authorize sufficient manpower to direct productivity improvements.

The first obstacle listed above is a crucial one and leads to the second and third. Without measurement, there can be no evaluation or productivity analysis. The outcome of productivity analysis is the diagnosis of productivity problems and the creation of corresponding solutions. Without productivity analysis, obviously, there can be no understanding of the problems and thus little understanding of how to improve productivity (obstacle #2). This leads to the third obstacle, inadequate support given to productivity improvement and hence, the lost opportunity for productivity improvement. But technologies such as decision support and expert systems can help analyze and diagnose the problems as well as recommend solutions. This paper explores where these technologies can be successfully used in the productivity management process.

2. Expert Systems

Expert systems are capable of incorporating a human expert's knowledge and analytical ability in a given domain and are able to explain the analytical methodology whenever the user questioned. A human expert is not certain or correct 100 percent of the time. Similarly, expert systems use a mechanism to handle uncertainty and incorporate user responses such as "Unknown" as well. Expert systems are different from conventional systems in two ways: They are more efficient at symbolic processing whereas conventional systems are efficient at numerical processing. In expert systems, the inference engine (or control structure) and knowledge base (or data) are kept separate, whereas in conventional systems they remain together. This separation enables the easier incremental refinement of the knowledge base. Potential benefits of expert systems include [3]: Improved decision making, more consistent decision making, reduced design or decision making time, improved training, operational cost savings, better use of expert time, improved product or service levels, and rare or dispersed knowledge captured.

2.1 Some Generic Application Areas of Expert Systems

Expert systems can be found in a wide variety of areas. Earlier applications were mainly in medicine and engineering. Expert system applications in medicine and engineering are vast; however, business applications have been becoming popular as well. Artificial intelligence and expert systems have not only generated great interest in medicine, science, and engineering. Expert systems have become very successful in facilitating the decision-making process in a wide variety of applications. Following this trend in medicine and engineering, expert systems have also been applied to business decision-making. As a result of this, a large amount of research on the topic of expert system applications in business has emerged [4][5][6][7].

Wong and Monaco [6] have identified 214 articles that report expert system application research in business. The findings suggest that expert systems are being used for a diverse range of functional activities, including production/ operations, finance, and information systems. Wong and Monaco [7] classify the literature on expert system applications in business by application area, generic problem area addressed, problem domain, level of management, level of task interdependence among other characteristics.

In another study, Eom [8] has presented that expert systems in business are most widely used in production/operations and scarcely in human resources. Some operations management application examples include scheduling factory orders, inventory and equipment tracking, shipping route optimization, material purchasing, and repair problem diagnosis [9].

The understanding of knowledge and its role are critical for an organization's success [10]. Evolution of web-based expert systems is an important trend that will change the nature of business as well. Widespread Internet access, availability of internet-compatible tools for expert system development, and portability of internet-based applications make them more powerful over their alternatives [11]. They are already being employed in applications, such as online advice [12], expert advice and problem-solving knowledge [13], and data management [14].

Web-based expert systems bring flexible data manipulation capabilities, intelligent fault diagnosis systems, highly efficient distribution schedules, and intelligent planning tools to assist communication and control tasks [15]. Similarly, in today's business, spreadsheets have become a fundamental tool [16]. Numerous Fortune 1000 companies have made use of knowledge-based systems to solve business problems, ranging from scheduling their manufacturing operations to managing their investment portfolios 17].

Most existing expert systems can be grouped into the categories of interpretation, diagnosis, prediction, design, planning, monitoring, debugging, repair, instruction, and control [18]. *Interpretation* infers descriptions from observable data. DENDRAL [19] is such an expert system. It infers a compound's molecular structure from mass spectral and nuclear response data. CSR ADVISOR [20] is an application in the marketing area and is used to tailor the knowledge about products and services to the needs of each client and then make it available to the customer service representatives. A PROLOG-based expert system predicts accurately complex compound properties from its structure [21]. COMVOB [22] is a knowledge-based system developed to determine the marginal value of building projects.

Diagnosis infers system malfunctions from observable data. Diagnostic expert systems relate these inferences to underlying causes. DELTA [23], for instance, helps identify and correct malfunctions in locomotives, whereas MYCIN [24] helps diagnose and treat bacterial infections. Expert systems are used in diagnosis in production processes such as automobile assembly or textile manufacturing [5]. A PROLOG-based expert system [25] assists in brain lesion diagnosis. A fuzzy expert system is developed [26] to diagnose the state of a pilot-scale wastewater treatment plant.

More and more of these decision support systems are used in customer relationship management, interactive marketing, and e-commerce [27]. Chiu [28] explains the use of a case-based reasoning system to predict customer-purchasing behavior. In a similar study, Song et al. [29] develop a methodology to detect, understand and adapt to changes of customer behavior in Internet shopping mall.

Design involves configuring objects under constraints. XCON [30], for instance, configures VAX computer systems. Expert systems also assist in the design of flexible manufacturing systems [5]. LIQUID [31] assists engineers in the preliminary design of liquid retaining structures. Alternate design, cost estimating, scheduling is another engineering use [32]. An example is design of ship systems automation [33].

Planning involves designing actions. FADES [34], for instance, is a facilities layout planning system. Expert systems have been used in production/operations in matching guests' room needs with the available rooms and in capacity and layout planning [5]. Productivity adjusted construction schedule is another area of application [35]. Furthermore, expert systems can be used to manage petroleum-contaminated sites [36]. In the production/ operations field, more advanced intelligent systems are used for efficient enterprise resource planning (ERP) maintenance [37].

Monitoring involves comparing current observations to expected outcomes. REACTOR [38] monitors instrument readings in a nuclear reactor looking for signs of an accident. An automatic stock control system can be monitored with the help of an expert system [5]. ALEES [39] is an expert system developed to be used by loan officers in evaluating agricultural loans.

Debugging evaluates source code to identify syntax errors, prescribe corrections, and make corrections. *Repair* is similar to debugging but its use is not limited to programming. TQMSTUNE [40] fine-tunes a triple quadruple mass spectrometer from mass spectral and nuclear response data. Repair and debugging of digital electric circuit cells is another application area [5]. CAST [41] is a rule-based expert system developed by Hewlett Packard to aid in configuring SAP implementations.

Instruction involves diagnosing learner weaknesses and prescribing remedial lessons. STEAMER [42] teaches the operation of a steam propulsion plant.

Finally, *control* involves maintaining a system in a predetermined state. It involves the interpretation, prediction, repair, and monitoring of system behavior. YES/MVS [43] helps computer operators monitor and control the MVS operating system. Control of manufacturing cells via expert systems is also mentioned [5]. IVAN [44], a case-based knowledge system, is used for pain control and symptom relief in advanced cancer. Expert systems are also used for blood pressure control [45].

When we focus in the production/operations management field, we also see applications in the area of productivity measurement and management. There is a rich body of knowledge on development, use, and impact of expert systems in decision sciences, including operations management [46][47][7] find that the most heavily researched area is production/operations. Their results also suggest *planning* is the most addressed problem area for production/operation expert systems. Other groups of applications concem *design*, *diagnosis*, and *repair*. A survey of UK organizations further depicted that expert systems are used for forecasting, problem analysis, fault diagnosis, routine activities, and decision support [48].

One concern of extreme importance to the operations management function and to the company overall is measuring the productivity. Expert systems have been suggested as a potential tool to increase productivity in automating many production functions, such as process planning, capacity planning, facility layout planning, design, diagnosis and troubleshooting, monitoring, and controlling production and operations management systems [49]. Expert systems mimic the heuristic methods that humans employ for production planning and control. The decisions of what level to make a given resource available and when to commit a given resource to a given unit of product can be assisted by expert systems to increase productivity [48]. An expert system that can measure the productivity of a company and interpret the results is essential and valuable to increase the productivity. Sumanth and Dedeoglu [50] have developed an expert system using the total productivity model.

In this section, various expert system applications, first from medicine and engineering, and then from business were summarized. Based on the literature review, production/operations has emerged as the business function where expert systems have been developed most widely. Total productivity measurement and control is one application area in operations management. In the next section, guidelines for appropriate applications will be outlined.

2.2 Guidelines for Appropriate Applications

Choosing an appropriate application domain is the important first step in developing an expert system. Some applications are more appropriate to specific cases than others because of their strengths in symbolic-processing and other capabilities. Prerau provides in detail a set of attributes, which includes technical as well as non-technical, such as corporate, issues [51]. Some characteristics of tasks best suited for expert systems applications are listed below [52]:

- Well-bound to prevent combinatorial explosions.
- Involves mainly symbolic processing (the processing of lists and symbols) as distinct from numerical processing.
- Takes from a few hours to a few weeks to solve.
- Performed frequently (i.e., it is not a once-in-a-lifetime activity).

- There is a significant difference between the best and worst performers of the task.

The next section discusses the potential application of expert systems in productivity management. The task characteristics listed thus far would be very useful in determining appropriate applications.

3. Expert Systems In Productivity Management

The steps in the productivity management process include measurement, interpretation, evaluation, choice of corrective or improvement solutions, and implementation of chosen solutions. The potential of expert systems applications at each stage of productivity management process is examined in this section. As alluded above, expert systems are beneficial for certain applications and not appropriate for others. Potential applications at the first three stages are discussed in detail; but the last two stages are left to the management's discretion because the number of solutions could be huge and the choices depend on so many other factors. Implementation stage is primarily a managerial action and planning for the next cycle of the process. First we look at the guidelines in determining the appropriateness of an expert systems application.

3.1 Measurement

(1) Selection of appropriate measurement model or models

Productivity measurement models can be classified in many ways. Rao classified all the models into three broad categories -- partial-factor, total-factor, and surrogate measures [53]. The model selected, however, depends largely upon the taxonomy or criteria one uses for classification. Sink et al. developed a comprehensive taxonomy for the classification of measurement models [54]. Their classification uses two criteria to categorize models, unit of analysis (from individual to national level) and scope of measurement or time frame (from minutes to years). Riel and Shin presented an expert systems approach to the model selection problem [55]. In the prototype presented, they have used nine attributes in order to choose among eleven measurement models.

In general, total-factor models seem most appropriate for measuring the overall productivity at the firm level. The Total Productivity Model (TPM) by Sumanth is one such model [56]. One of the more recent approaches links productivity performance directly to the bottom line of the firm. MFPMM is such a model. It is, in fact, a variation of the American Productivity Center (APC) model [57] [58]. "Profitability = Productivity + Price Recovery" (PPP) procedure, introduced by Miller, is yet another model [59]. The PPP and the APC model are similar in some respects; both link productivity to the bottom line of the firm, use the same input data, and result in the same value from their profitability, productivity, and price recovery formulas when applied in certain situations. However, there are substantial differences between the APC model and the PPP model [60].

Whether the criteria used here by Riel and Shin [55] are appropriate or not, and the set of models used is sufficient or not, the application of using an expert system for selecting a measurement model itself is very appropriate based on the guidelines presented in the last section.

(2) Setting up the measurement system

Once an appropriate model is chosen, it should be set up or implemented. Some models are easy to set up and use whereas others require a considerable amount of time and skill. For instance, it is not easy to set up a measurement system using a model such as PPP. It is best set up as a spreadsheet-based system. Even then, using different formulas in different cells can be difficult. Hence, an expert system application to generate such a measurement system would be of great assistance. The task is well bounded and involves mainly symbolic processing. Because of the scarcity of experts within organizations who not only know the model well but also are competent at using complex formulas in a spreadsheet, it seems to be a good task for an expert system application.

(3) Gathering of relevant data

Implementing such a measurement model requires gathering any two of quantity, price, or value of each input and output. Inputs are categorized as material, labor, energy, capital, and miscellaneous resources. Outputs are categorized into product lines. Then, a "typical" period or optimal [53] data is chosen for the base period. To measure the productivity performance of a particular period, the same type of data is gathered for that period. These data are then used in the model to obtain the productivity, profitability, and price recovery contributions of each element and category in dollar terms. In addition, the model can also generate measures such as deflated gross profit and deflated net sales, which are also useful in the productivity analysis.

The data is dependent on the model chosen. The frequency of data gathering also depends on the situation. Organizations may want to monitor performance monthly, quarterly, or yearly. The data may have to be collected manually or it may be available on a computer in a proper format for the measurement system to use it. In any case, this task seems not suitable for expert systems application.

(4) Generation of performance results

Once the data is fed into the measurement system, the results should be computed by the system. It is essentially a number crunching job and is not suitable for expert systems application.

In summary, at the measurement phase, there are two possible expert systems applications, for selecting appropriate models and setting up a measurement system.

3. 2 Interpretation

Interpretation is the phase between measurement and evaluation. It involves making tentative assessments based upon the numbers generated by the measurement model [62]. For example, Table 1 shows the contributions of labor and capital using a model such as PPP. These figures appear to reveal a problem with the price recovery contribution of labor (-$3,500), indicating that labor wage rates were increased or the price of outputs was decreased or both. The labor wage increase seems to be much higher than could be compensated for by the labor productivity and the product price increases, thus ultimately leading to negative profitability. These are some of the tentative assessments that can be made from Table 1.

Table 1 Contributions of Labor and Capital

	Productivity	Price Recovery	Profitability
Labor	2,000	-3,500	-1,500
Capital	1,000	0	1,000
Total	**3,000**	**-3,500**	**-500**

An expert systems application for interpretation seems appropriate because there are several existing expert systems that fall into the category of interpretation. There are three steps in the interpretation of measurement results:

1. Identification of performance results
2. Assessment of performance significance
3. Interpretation of numerical results into a performance story.

These steps are discussed next with examples from an expert system prototype called PET (Productivity Evaluation Technology) [62].

(1) Identification of Performance Results

The expert system should be able to identify changes in performance results. The primary source of these results is the measurement system. The measurement system may be based on any model such as PPP, APC, MFPMM, TPM, or the Objectives Matrix. The expert system should, therefore, be able to execute this measurement system, and obtain the relevant results and data from the system. The performance changes may be point-to-point or other data patterns such as trends. This identification is not limited to one level, but should take place at various levels such as the macro-level, category-level, and element-level performance. Moreover, it should not be limited to the results of a measurement system such as productivity, price recovery, or profitability contributions alone. It also should be able to use indexes, reported and deflated sales and profit margins, results from other models such as LP models and simulation models, sources such as accounting data, and the user. The ability to access and use data from various sources can facilitate more precise identification of problems.

(2) Assessment of Performance Significance

Once the performance results are identified, a generic system should be able to assess the significance of the performance changes. Information about problem significance allows problems to be ranked according to their severity. Without such information, minor problems and serious problems would receive the same attention. Moreover, some variations in performance may be purely random and without any assignable causes. Hence, an expert system for productivity analysis should be able to identify non-random variations and make a value judgment about the significance of the problem such as very serious, serious, significant, moderate, minor, insignificant or no problem. Conversion of numerical values into such descriptive terms makes them more meaningful to a manager and represents an extremely useful feature from a management standpoint. Without this capability, a great deal of time must be spent in arriving at the same results. As mentioned earlier, knowledge-based technology is efficient for symbolic processing. Hence, such value-judgment features can be easily handled with knowledge-based technology.

(3) Interpretation of Numerical Results into a Performance Story

As shown above, value judgments are very useful in analyzing productivity performance. They would be even more useful if the results were presented to the user as a complete performance "story" rather than just a number or a single word, such as SERIOUS. It is valuable for the system to display at least a one-sentence statement such as; "There is a SERIOUS PROFITABILITY-PROBLEM with WOOD-WORKERS with a 0.7 certainty." However, a performance story needs to be much more than one sentence. A comprehensive narrative portrayal is vital if an expert system is to provide quick, accurate and understandable productivity analysis to a manager.

3.3 Evaluation

Interpretation, although useful, is just one step in the analysis. The numbers and ratios resulting from a model yield nothing more than a set of symptoms. Evaluation leads to identifying the real causes of poor productivity, price recovery, and profitability. To find the causes of symptoms, evaluation requires interaction between the productivity analyst and the manager of the profit center. The answers are not obvious because they depend upon many variables such as product-mix, volume, and resource-mix, any of which might have changed because of a number of factors such as market conditions, employee morale, union problems, safety, overtime, scheduling problems, and inventory problems.

(1) Association of Causes with Effects

A generic system for productivity analysis should be able to determine the causes of identified problems. For example, if labor productivity has been identified as a problem, then the system should be able to determine that the problem is motivation, training or whatever is the case. An expert system can determine such a cause by gathering information electronically from company databases or manually from the user. For example, if absenteeism and tardiness point to motivation as the cause, actual absenteeism and tardiness data for recent periods can be obtained from company databases. If the relevant data is not in the company databases, the user must provide it.

(2) Causes of Resource Inefficiencies

In general, resources can be categorized as labor, material, energy, capital, and other. There could be a list of problems identified in each of these resource categories.

There are several successful expert systems now in use in the area of diagnosis. Since evaluation involves determining underlying causes, it is a very appropriate expert systems application.

3.4 Selection of Improvement Solutions

A generic system for productivity analysis should be able to recommend corrective actions based on the causes identified above. A simple cause and treatment might be, for example, that if lack of training is lowering labor productivity, then training is the appropriate corrective action. However, a comprehensive treatment may not be that simple. In the first place, there may not be a single cause. Sometimes, when several causes are put together, there may be a single appropriate treatment, while on the other hand, one cause may require several types of treatments. So a specific treatment for each cause may not be wise. An expert systems application for choosing the right solutions to correct the identified problems seems ideal.

3.5 Implementing Improvement Solutions

Implementing Improvement Solutions involves management action. Some of the improvement solutions may include expert systems applications, of which there are virtually an unlimited number of applications. For instance, if the problem is with layout, one could use an expert system such as *FADES*. There are several expert systems applications for improving scheduling, maintenance, forecasting, etc.

4. Conclusion

Although productivity management is essential for long-term survival of a business, there are serious obstacles to its practice because many managers do not have the skills or time to analyze productivity and take necessary corrective actions in time. The application of expert systems technology can solve these problems. Expert systems can assist managers in nearly all phases of the productivity management process. This paper has described each stage of this process and discussed the fitness of expert systems applications. Examples of existing prototypes illustrate the possibilities and the strengths of these applications. This research may lead to the development of several new expert systems applications, and as a result, improved productivity in the business world.

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