Development and Cost-Effective Application of an Expert System for Improving Productivity: A Real-World Case Study

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This paper presents a case study of an expert system combining a knowledge-based system and regression analysis to support decision making involved in improving the productivity of an organization. A pharmaceutical distributor in Taiwan is used as an example to illustrate the development and application of an expert system to tackle the daily decision problem of handling uncertainty in carrying out delivery tasks. Regression analysis is used as a method to predict the working time of drivers undertaking the delivery tasks. The application of a knowledge-based system coupled with the use of regression analysis is proposed to balance the workload, increase capabilities of handling more orders, improve productivity, ensure decision consistency, and reduce relevant costs. To determine whether or not the proposed expert system will be technically feasible and cost-effective, a systematic way of predicting the success or failure of the system is implemented. It is found that the project would be worth much more than what it would cost. Thus, the proposed expert system is economically justified.

Introduction

In recent years, Expert Systems (ES) have emerged as powerful tools for the design and operation of many business systems. Many organizations, private and public, are developing ES that help their managers make better decisions. ES are computer programs that emulate certain functions of human expertise. An ES usually contains a knowledge base that consists of facts and relationships about a specific problem domain and some rules of thumb or judgmental knowledge used by one or more experts for solving the problem at hand (Barsanti, 1990).

ES cannot solve every problem defined, but they can be practical and cost-effective in specific areas. As with any computer program, ES are good at quickly and accurately processing large-quantities of data and performing rote tasks. The potential for using an ES will differ across industries, businesses, and functional areas. In addition, managerial perceptions and attitudes are important issues that need to be considered when an ES is launched. Financial and accounting professionals believe that ES provide financial benefits such as increased productivity, greater sales volume, and reduced equipment and staff costs (Anderson & Bernard, 1986).

Due to its nature, an ES has demonstrated the potential for increasing the productivity of organizations by improving business processes and supporting end-user tasks (Byrd, 1992; Guimaraes, Yoon, & Clevenson, 1996). Although much speculation and anecdotal evidence exist suggesting that ES applications are being developed in today's organizations, there is little information on the development of ES in actual organizational sectors for improving their productivity. Since such systems are custom-developed, it is very difficult to purchase a ready-made system that meets an exact need. In-house developments will be imperative when a flexible application of ES is desired or when the relevant knowledge is proprietary or sensitive to the organization (Martinsons, 1995).

This paper is intended to be a guide to the development and application of ES for improving the productivity of organizations. This study also presents approaches that help organizations judge the applicability and reliability, focus on the proposed benefits, and justify the costs of implementation. A pharmaceutical distributor in Taiwan is used for purposes of illustration.

Statement of the Problem Situation

ABC Company is the key provider of distribution, marketing, and manufacturing services to more than 125 international healthcare corporations in the Asia-Pacific region. During the past decade, ABC Company has succeeded in attracting more than 20 international pharmaceutical companies, performing a wide range of value-added services. Today, the company has become one of the largest independent distributors of pharmaceuticals in Taiwan and one of the largest promoters of products to retail pharmacies.

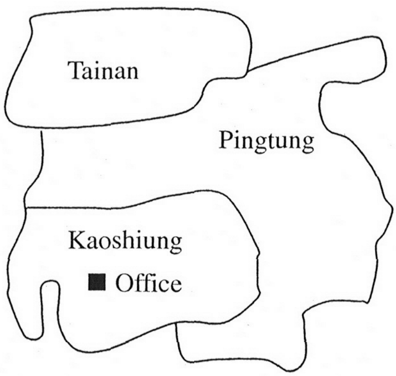
On behalf of ABC Company, Survey Research Taiwan (SRT) recently interviewed more than 180 general practitioners and small hospitals. The purpose of the survey was to identify the current and future levels of satisfaction and importance of specific customer service attributes, such as order processing and delivery, to those customer groups. The result of the survey indicates that promptness of delivery is considered the most important service that a supplier is expected to provide. More than 60% of the customers interviewed expect delivery within 24 hours of order taking. Moreover, customer satisfaction drops to 38% if the products are not delivered with that 24-hour time frame.

The major concern of ABC Company is related to its distribution system in South Taiwan. The branch office in Kaoshiung, adopting just-in-time (JIT) production, receives products from the main warehouse in Taipei on a daily basis according to the orders received from the customers in Kaoshiung (Area K), Pingtung (Area P), and Tainan (Area T) (see Figure 1). The products that the branch office receives have been classified by areas before they are delivered from the main warehouse. The branch office, operating with zero inventories, has four trucks and five drivers deliver products to the customers in these areas. Two drivers undertake the delivery task for Area K; one driver delivers to Area P; two drivers deliver to Area T. Three trucks are used to deliver products to these three areas, respectively; the fourth truck is used only if any of the other trucks is overloaded. Although the company's sales in South Taiwan have been increasing in recent years, its labor and equipment remain unchanged. As a result, its products sometimes cannot be delivered within the 24 hours of order taking as expected by most of its customers. Due to its limited budget, the company wants to minimize overtime and satisfy all of the demand requirements without increasing its labor and equipment. Furthermore, the daily workload of each driver is unequal because of different demand requirements among the three areas. The company is concerned about the fact that each driver receives the same amount of incentives regardless of his workload as long as he completes the delivery assignment within regular hours per day. The management also intends to speed up delivery and reduce transportation costs, which can stimulate sales.

The information system currently used by ABC Company assigns the delivery task to each driver according to the individual's delivery area. It is evident that a more structural approach for handling the uncertainty of delivery tasks is required to support managerial judgments and to improve the effectiveness of decision making. The IBM PC is the target-user computer used by the company. The management would like to tackle the distribution issues by developing an ES as a complement of the existing system. The proposed ES would fulfill the following objectives:

- More efficient use of the trucks
- Minimization of overtime costs
- Equal workload for each driver
- Reduced transportation costs
- Increased capabilities of handling more orders
- Faster delivery times/increased productivity
- Consistent decisions

Figure 1. Map of South Taiwan



Methodology

Information Flow

Before an ES is developed, it is necessary to understand how the information is received and converted into the final decision. The current information flow of ABC Company is shown in Figure 2. The decision maker, the division manager for South Taiwan in this case, receives raw data, such as the number of orders received for each specified area, directly from the main warehouse in Taipei. These raw data also pass through all drivers (1 to N) and are converted into certain knowledge (e.g., the probable working time needed to finish each workload). The decision maker then acquires this knowledge from the drivers. He makes the final decision on scheduling the delivery tasks after evaluating all the relevant data and knowledge. However, knowledge provided by the drivers can be very subjective and unstructured. The decision-making process is also very individualized. It is difficult to duplicate and transfer. As a result, the decision maker may not uphold the consistency of his decisions.

An ES is proposed for ABC Company to improve problem-solving capabilities of the decision maker. As indicated in Figure 3, the drivers' knowledge is collected and analyzed into an organized knowledge base, and the raw data are converted into useful information through a mathematical model. The knowledge base interacts with the mathematical model to form an ES. The final decision can then be made according to the output from the ES.

Of the techniques developed from research about artificial intelligence, knowledge-based systems (KBS), neural networks (NNTs) and fuzzy logic (FL) have important business applications. All of these three techniques contain properties that work efficiently on certain domains of data that can be categorized either symbolically or

Figure 2. Current Information Flow

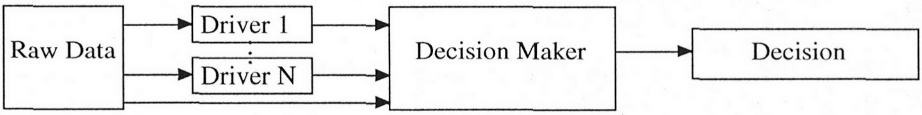
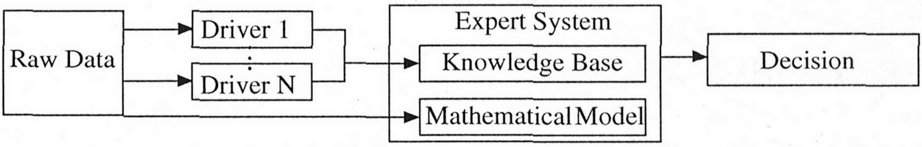


Figure 3. Proposed Information Flow



numerically, and either structurally or unstructurally. Specifically, KBS represent a structured-symbolic approach; FL is especially useful for handling structured-numeric data; NNTs use an unstructured-numeric approach (Skowronski & Shaw, 1992). However, in some cases it is possible to use a blend of these technologies to achieve desired results. The raw data in this study are structured-symbolic (e.g., the knowledge acquired from the drivers) and structured-numeric (e.g., the number of invoices issued). Accordingly, a KBS will be employed to manage structured-symbolic data. To simplify the process of predicting the working time of each driver, regression analysis, rather than FL, will be used to develop a mathematical model that handles structured-numeric data. The proposed ES, a combination of a KBS and regression analysis, will be applied to reach the final decision on assigning the delivery tasks to each driver.

Knowledge Acquisition

The first approach that needs to be addressed for the development of an ES is knowledge acquisition, which involves identifying the specific knowledge that an expert uses in solving a problem. One of the most important strategies of knowledge acquisition is the interview (Diederich, Ruhmann, & May, 1987). In this case study, a knowledge engineer used the interview technique to elicit the knowledge the drivers and the division manager for South Taiwan used to schedule the daily tasks. Once the knowledge engineer acquired the relevant data and information, he then interpreted the data and information and drew conclusions as to what might be the drivers' and the manager's underlying knowledge and reasoning processes. These processes are as follows:

- Three trucks are used to deliver products to Area K, Area P, Area T, respectively.
- Whenever the truck used to deliver products to Area T is overloaded, the drivers assigned to this area have the priority to use the fourth truck because Area T is the farthest from the branch office in Area K than are the other regions. If the truck used to deliver products to Area T is not overloaded, but the truck to Area K is overloaded and predicted to be used overtime, the fourth truck will be used additionally for delivery to Area K so that none of the trucks will be overloaded.
- The truck which is used to deliver products to Area P has never been overloaded, so the fourth truck has never been needed for this region.
- All trucks must return to the branch office in Area K after the drivers finish delivery.
- Since the branch office is located in Area K, the truck which is used to deliver products to this region can return to the office and reload several times per day.
- Only one driver is allowed to go on leave per day.

Estimation Procedure

A popular multiple regression technique called stepwise regression analysis is used to predict the working time of each driver. This approach allows the examination of the contribution of each predictor variable to the regression model and the selection of variables that maximize the prediction with the smallest number of variables employed. One of the predictor variables used in the analysis is the number of invoices issued. The other variables are the customers who are either isolated and/or need special services, and they are grouped based on their locations (Area K, Area P, or Area T). A representative sample of 60 working days is chosen for the purposes of this analysis.

The regression equations will be used to predict the working time of each driver if the value of each independent variable is specified. To determine if a driver is working more or less than the regular eight hours per day, a 95% confidence level is chosen for the one-tailed test. Accordingly, overtime is defined as working time greater than 540 (480 minutes plus 60 minutes of lunch time) + 1.645σ; undertime is defined as working time less than 540 - 1.645σ. If a driver is predicted to be working undertime, he will be assigned to help the one working overtime so as to minimize overtime and balance the workload of each driver.

Development of the Expert System

The conceptualized knowledge acquired from the division manager and the drivers as described earlier can be refined to a series of if-then statements (rules). The interpretation of a rule is that if the antecedent can be satisfied, then the consequent can also be satisfied. When the consequent defines an action, the effect of satisfying the antecedent is to schedule the action for execution. When the consequent defines a conclusion, the effect is to infer the conclusion (Hayes-Roth, 1985). On the basis of the conditional if-then rules, there is an unique solution for each condition. For example, ***if*** X is A, ***then*** Y is B. However, different conditions may have the same solution. When multiple dependent conditions occur simultaneously, rules with multiple antecedents combined with the intersection operator ***"and"*** are used (Chang, Yeh, & Cheng, 1998). For example, ***if*** X is A ***and*** Z is C, ***then*** Y is B. The rules will be used to drive the development of the model implemented in the ES shell. After identifying the shell available for the target-user computer used by the company, the programmer needs only to insert the rules in order to build the ES.

Predicting Success or Failure

Coakes and Merchant (1996) conducted a survey intending to determine reasons why organizations had chosen to purchase or develop ES and to clarify the system's perceived benefits to the firms. The results indicate that companies mainly use ES for routine decision-making in order to increase efficiency and maintain competitiveness and that cost-effectiveness and perceived business benefits are the main reasons given for purchasing or developing an ES.

The cost-benefit criterion, or theme, is central in designing ES. Elaborate systems are expensive in terms of time and money. The costs of educating managers and other personnel must be considered. More sophisticated systems like ES are installed only if managers believe that collective operations will be sufficiently improved in a net cost-benefit sense. Moreover, managers must consider the operational feasibility of a potential

ES. They must ensure that ES applications can be developed and operated in a cost-effective manner and sufficiently validated to protect against erroneous outputs.

To determine whether the proposed ES will be technically feasible and cost-effective, a systematic way of predicting the success or failure of the proposed system is employed. If the application proves feasible and worth the cost, the information generated during the decision phase can be then used to speed the development process.

Analysis and Evaluation

Regression Models

The coefficient of multiple determination (R^2) is a measure commonly used in regression analysis to indicate the accuracy of the regression model (Montgomery and Peck, 1992). In all regression models developed in this study, R^2 ranges from 0.798 to 0.847, which is quite satisfactory, given the cross-sectional nature of the data sample. Furthermore, the regression coefficients (β) of predictor variables in all the models remain stable in their magnitude and sign across the models. Therefore, estimates are stable and consistent.

With the model estimation completed, the regression variate specified, and the diagnostic tests administered that confirm the appropriateness of the results, the predictive equation can be interpreted. After a number of predictor variables were investigated, the predictive equations are:

$$Y_A = 244.864 + 5.365A_1 + 35.666A_3 + 25.093A_4 + 57.523A_5$$
$$Y_B = 272.442 + 6.347B_1 + 36.453B_2 + 37.452B_4 + 54.279B_6$$
$$Y_C = 245.451 + 6.221C_1 + 51.203C_3 + 32.972C_5 + 34.210C_8$$

where:

Y_A, Y_B and Y_C are estimated working time of each driver in charge of Area K, P, and T, respectively.

A_1, B_1 and C_1 are number of invoices issued for Area K, P, and T, respectively.

$A_3 = 1$ if Kao-Yi Hospital places an order, 0 otherwise.

$A_4 = 1$ if any customer in Chi-Gin places an order, 0 otherwise.

$A_5 = 1$ if any customer in Hsiao-Kang places an order, 0 otherwise.

$B_2 = 1$ if any customer in Chi-Shan places an order, 0 otherwise.

$B_4 = 1$ if any customer in Lin-Yuan places an order, 0 otherwise.

$B_6 = 1$ if any customer in Tzu-Kuan places an order, 0 otherwise.

$C_3 = 1$ if Chi-Mei Hospital places an order, 0 otherwise.

$C_5 = 1$ if Cheng-Kung Hospital places an order, 0 otherwise.

$C_8 = 1$ if any customer in Hsin-Ying places an order, 0 otherwise.

Kao-Yi, Chi-Mei and Cheng-Kung Hospitals: Customers with the history of ordering large quantities of products.

Chi-Gin and Hsiao-Kang: Towns located on the border of Area K requiring extra delivery time.

Chi-Shan, Lin-Yuan, and Tzu-Kuan: Towns located on the border of Area P requiring extra delivery time.

Hsin-Ying: Town located on the border of Area T requiring extra delivery time.

The regression equations will be used to predict the working time of each driver if the value of each independent variable is known. As mentioned earlier, two drivers undertake the delivery task for Area K, one driver for Area P, and two drivers for Area T; the fourth truck would be used only if any of the other trucks is overloaded. According to the underlying knowledge of the drivers, the working time will increase by 10% if one of the drivers in charge of delivery to Area K or Area T is absent. The working time will decrease by 30% if the fourth truck is also used. Therefore, when necessary, the predicted working time should be adjusted to reflect these differences.

Description of the Expert System

The next pages present the steps of building the knowledge base. The process of organizing the knowledge acquired from the division manger and the drivers is described in such a way that it can be understood and then translated into rules. First, the division manager and the drivers are asked the following questions:

- Is any driver absent? (Yes/No)
- Is the truck which is used to deliver products to Area T predicted to be overloaded? (Yes/No)
- Is the truck which is used to deliver products to Area K predicted to be overloaded? (Yes/No)
- Is the estimated working time of each driver who undertakes the delivery task for Area K greater than $540 + 1.645\sigma$? (Yes/No)

Whether or not the truck is overloaded or not depends on the drivers' judgment. Although subjective, this judgment appears to be the most cost-effective method to predict the workload of each driver. The answers to above questions are then categorized into the following conditions.

Condition 1: None of the drivers is absent.
Condition 2: The truck used to deliver goods to Area T is predicted to be overloaded.
Condition 3: The truck used to deliver goods to Area K is predicted to be overloaded, and the estimated working time of each driver in charge of Area K is greater than $540 + 1.645\sigma$.
Condition 4: One driver is absent.

Under different combinations of these conditions, the knowledge acquired from the division manager and the drivers can be refined to a series of if-then statements (rules) as follows:

<u>Statement 1</u>
If: Condition 1 and Condition 2 is present,
Then: Consequent 1 and Conclusion 1 are referred.

<u>Statement 2</u>
If: Condition 1 and Condition 3 are present, and Condition 2 is not present,
Then: Consequent 2 and Conclusion 2 are referred.

Statement 3
If: Condition 1 is present, and Condition 2 and Condition 3 are not present,
Then: Consequent 3 and Conclusion 3 are referred.

Statement 4
If: Condition 4 and Condition 2 are present,
Then: Consequent 4 and Conclusion 1 are referred.

Statement 5
If: Condition 4 and Condition 3 are present, and Condition 2 is not present,
Then: Consequent 5 and Conclusion 2 are referred.

Statement 6
If: Condition 4 is present, and Condition 2 and Condition 3 are not present,
Then: Consequent 6 and Conclusion 3 are referred.

Table 1 shows the six Consequents that relate to the six if-then statements, respectively. Consequents 1, 2, 4, and 5 indicate the areas for which the fourth truck will be used. Consequents 4, 5, and 6 present the adjustment of driver assignment due to the absence of a driver. These six Consequents define three types of Conclusions. Table 2 presents Conclusion 1 that proposes the corresponding actions based on both the conditions in Statements 1 and 4, and Consequents 1 and 4. The fourth truck will be used to share delivery of products to Area T (see Consequents 1 and 4) so that none of the trucks will be overloaded. The drivers assigned to Area T will complete the task in less than regular hours due to the use of two trucks for delivery. Table 3 shows Conclusion 2 that defines the corresponding actions based on both the conditions in Statements 2 and 5, and Consequents 2 and 5. The fourth truck will be used additionally for delivery of products to Area K (see Consequents 2 and 5) so that none of the trucks will be overloaded. The drivers assigned to Area K will finish the job in less than regular hours due to the use of two trucks for delivery. Table 4 presents Conclusion 3 that describes the corresponding actions based on both the conditions in Statements 3 and 6, and Consequents 3 and 6. Although Conclusion 3 also includes some overtime cases, the fourth truck will not be used since no truck is overloaded and since the benefits of time savings are not going to be worth the cost of operating and maintaining the truck. Tables 2-4 are followed by the explanation of workload adjustments recommended for various situations.

Table 1. Consequent (C)

	C1	C2	C3	C4	C5	C6
No. of truck/No. of driver to Area K	1/2	2*/2	1/2	1/1	2*/2	1/1
No. of truck/No. of driver to Area P	1/1	1/1	1/1	1/1	1/1	1/1
No. of truck/No. of driver to Area T	2*/2	1/2	1/2	2*/2	1/1	1/2

Note: An asterisk (*) indicates the use of the fourth truck.

Table 2. Conclusion 1

Area K	Area P	Area T	Adjustment
U	U or N	U	N/A
U	O	U	P>K or P>T
N	U or N	U	N/A
N	O	U	P>T
O	U	U	K>P or K>T
O	N	U	K>T
O	O	U	K>T and P>T

Table 3. Conclusion 2

Area K	Area P	Area T	Adjustment
U	U	U or N	N/A
U	U	O	T>P
U	N	U or N	N/A
U	N	O	T>P>K
U	O	U	P>K or P>T
U	O	N or O	P>K

Table 4. Conclusion 3

Area K	Area P	Area T	Adjustment
U	U	U or N	N/A
U	U	O	T>P
U	N	U or N	N/A
U	N	O	T>P>K
U	O	U	P>K or P>T
U	O	Nor O	P>K
N	U	U or N	N/A
N	U	O	T>P
N	N	U or N or O	N/A
N	O	U	P>T
N	O	N or O	N/A
O	U	U	K>P or K>T
O	U	N	K>P
O	U	O	K>P and T>P
O	N	U	K>T
O	N	N or O	N/A
O	O	U	K>T and P>T
O	O	N or O	N/A

U indicates undertime, which is defined as predicted working time less than 540 - 1.645σ.

N indicates normal time, which is defined as predicted working time no less than 540 - 1.645σ and no greater than 540 + 1.645σ.

O indicates overtime, which is defined as predicted working time greater than 540 + 1.645σ.

K>P indicates that part of the orders from Area K will be delivered by the truck that is used to deliver products to Area P until one or more of the following criteria is/are met:

1. The estimated working time, after adjustment, of the driver for Area P is greater than that for Area K.
2. The estimated working time, after adjustment, of the driver for Area P is greater than 540.
3. The estimated working time, after adjustment, of each driver for Area K is less than 540.

Note: These guidelines of workload adjustments are also applied to K>T, P>K, P>T, and T>P.

K>T and P>T indicates that part of the orders from Area K and Area P will be delivered by the truck(s) used to deliver products to Area T until one or more of the following criteria is/are met:

1. The estimated working time, after adjustment, of each driver for Area T is greater than that for Area K and that for Area P.
2. The estimated working time, after adjustment, of each driver for Area T is greater than 540.
3. Both the estimated working time, after adjustment, of each driver for Area K and that of the driver for Area P are less than 540.

Note: These guidelines of workload adjustments are also applied to “K>P and T>P”.

K>P or K>T indicates that part of the orders from Area K will be delivered by either the truck that is used to deliver products to Area P or the truck(s) to Area T, depending on which area’s driver has a lower predicted working time, until one or more of the following criteria is/are met:

1. The estimated working time, after adjustment, of each driver for Area K is less than that for the selected area.
2. The estimated working time, after adjustment, of each driver for Area K is less than 540.
3. The estimated working time, after adjustment, of each driver for the selected area is greater than 540.

Note: These guidelines of workload adjustments are also applied to “P>K or P>T”.

T>P>K indicates that part of the orders from Area T will be delivered by the truck that is used to deliver products to Area P and that part of the orders from Area P will be delivered by the truck(s) to Area K simultaneously until one or more of the following criteria is/are met:

1. The estimated working time, after adjustment, of each driver for Area T is less than that for Area K.
2. The estimated working time, after adjustment, of each driver for Area T is less than 540.
3. The estimated working time, after adjustment, of each driver for Area K is greater than 540.

Note: The reason for using the truck to Area P as an intermediary is that it will be very inefficient if the truck to Area K is used to share delivery of products to Area T considering that Area P is located in the middle of Area K and Area T and that the loading area for all trucks is located at the branch office in Area K.

N/A indicates that no adjustment is needed.

Results From Success or Failure Assessment

This study uses the Hartman (1993) model for predicting the success or failure of the proposed ES. The methods focus on eliminating obviously unsuitable problems and performing risk assessments and cost evaluations of the system.

Applicability and Risk

The applicability factor (see Table 5) incorporates the lessons learned in planning and implementing the ES. The questions relate to the development and application of the system, types of problems being solved, and the tolerance to "human" error inherent in the system that emulates human decisions. Each question has a range of possible answers corresponding to how well or poorly it is satisfied by the proposed system. The 1 to 10 score represents bad to good. Highly applicable systems have scores near 10.

When using this questionnaire on applicability, the developer, division manager, distribution manager, and operations manager score each question, total the scores, and normalize the factor by the maximum possible score. The normalized range is from 0.1 to 1.0. Any number of questions can be applied and normalized.

The questionnaire on the risks in implementation, as shown in Table 6, is constructed and used in the same way as the one on applicability. This time the 1 to 10 score represents good to bad. A low-risk system has a low score, and high scores represent greater implementation risks (Hartman, 1993; Kozlov, 1988; Leonard-Barton & Sviokla, 1988).

Table 5. Questionnaire on Applicability of the Problem

- Is this a high value application? (1=No; 10=Yes)
- Does the program provide a large increase in capability over what is now being done? (1=No; 10=Yes)
- Do you have people ready to use the expert system? (1=No; 10=Yes)
- Can the problem be easily solved by the experts (i.e., the division manager and the drivers) in your company? (1=No; 10=Yes)
- Can the problem-solving skills be readily taught to new people? (1=No; 10=Yes)
- Is there only one right answer? (1=No; 10=Yes)
- Can "human" error be tolerated in the result? (1=No; 10=Yes)
- Does the problem use computer-transferred data? (1=No; 10=Yes)
- Can the problem-solving method be written as straight forward rules of thumb? (1=No; 10=Yes)

Costs versus Benefits

It takes great effort to derive detailed rules for use in a large ES, and the development of the final ES is, as a consequence, much more costly. The product development stage will usually take 30-50 percent of the total costs for small and large ES, respectively (Hartman, 1993). The proposed ES will be installed only if managers believe that the distribution system will be sufficiently improved in a net cost-benefit sense. Tables 7 and 8 present the relevant costs and benefits of developing and implementing the proposed ES for ABC Company, respectively.

Weighting Factors

The applicability and risk factors are combined to provide a single weighting, which is applied to the benefit to cost ratio. This weighting enhances the assessment of ES that have high applicability and low risk. Systems that have low applicability and high risk have a decreased weighting factor. In addition, the expenses associated with the development and implementation of ES need to be weighted against the benefits. The combined effect of the applicability and risk factors increases the weighted benefit/cost ratio by 10 to 1 for ES that prove feasible or reduces it by the same order of magnitude for highly unsuitable and risky systems.

Weighted Benefit/Cost Ratios

The chance of success of the ES for ABC Company can be predicted by applying the applicability/risk factor to the benefit/cost ratio. Table 9 presents the data previously developed and the unweighted and weighted results on the success or failure graph. This graph extends the concepts of cost-effectiveness to include uncertainty. The results indicate that the benefit/cost ratio is 11.88 and that the weighted benefit/cost ratio is 40.29, implying that the proposed ES is technically feasible and cost-effective. This is clearly a good prospect for implementation.

Table 6. Questionnaire on the Risks in Implementation

- Is your upper management enthusiastic about an Expert System solution to this problem and are they willing to commit needed resources? (1=Yes; 10=No)
- Has an expert system like this been implemented by your company before? (1=Yes; 10=No)
- Do you have enthusiastic experts available to work on this implementation? (1=Yes; 10=No)
- Do your company's people have the artificial intelligence skills to develop and maintain this expert system? (1=Yes; 10=No)
- Is this problem within the State of the Art? (1=At; 10=Beyond)
- Is the problem constantly changing? (1=No; 10=Yes)
- Is it easy to get computer-readable data for this problem? (1=Yes; 10=No)
- Are "real time" answers required? (1=No; 10=Yes)
- Would the problem and/or data fit on small, medium, or large computer? (1=Small; 5=Medium; 10=Large)

Table 7. Costs of Developing and Implementing an ES for ABC Company

- Development costs.
- Cost of hardware.
- Loss of income tax savings due to depreciation on a new truck.
- Loss of eventual terminal disposal price of a new truck.
- Recurring operating costs.
- Testing to insure correct operation.
- Testing to identify future changes needed.
- Training for the users.
- Follow-up maintenance.

Table 8. Benefits of Implementing an Expert System for ABC Company

- Cost savings of not acquiring a new truck.
- Cost savings of not hiring a new driver.
- More efficient use of the trucks.
- Minimization of overtime costs.
- Equal workload for each driver.
- Reduction of transportation costs.
- Increased capabilities of handling more orders.
- Faster delivery times/increased productivity.
- Consistent decisions.

Table 9. Success or Failu re Assessment for ABC Company

• Applicability Factor	(A)	= 0.78		
• Risk Factor	(R)	= 0.23	100__	SUCCESS
• Applicability/Risk	(A/R)	= 3.39		
• Benefit ($000)	(B)	= $3,672	10__	____________
• Costs ($000)	(C)	= $309		QUESTIONABLE
• Benefit/Cost Ratio	(B/C)	= 11.88	1__	____________
• Weighted Benefit/Cost Ratio	(A/R)x(B/C)	= 40.29	0.1__	FAILURE

Weighted and Unweighted Benefit/Cost Ratios

Limitations

This study, as with any other study, has limitations that need to be discussed. The first limitation is the methods used to solve the delivery problems in this study. Regression analysis is used as a method to predict the working time of each driver, coupled with the use of the KBS to balance the workload. The issues can also be treated as traveling salesman problems (TSP) that can be solved by a genetic algorithm (Fu & Su, 2000; Qu & Sun, 1999). A genetic algorithm would generate better solutions than the methods used in the present study. However, it is difficult to build a matrix to define the relationships between any two customers in terms of the following conditions:

1. For an accurate prediction of the working time of each driver, it is necessary to collect the relevant data pertaining to both the distance between customers, and the average driving speed of the trucks. (Time is calculated as distance divided by average speed.) However, the company has approximately 2,000 customers in South Taiwan. It is fairly time-consuming to collect the complete 1,999,000 (C_2^{2000}) sets of data pertaining to the distance between customers. Furthermore, the data regarding an average driving speed are not attainable due to the versatile traffic volume.
2. Customers might request special services individually. For example, some expect delivery in the morning; on the other hand, some expect delivery in the afternoon.

It is almost impossible to maintain a database to provide all of the information needed. Thus, a genetic algorithm is not used to solve the delivery problems.

The second limitation is related to the adjustment of the workload. The use of the ES helps the division manager make better decisions on when the fourth truck will be needed and which truck will be used to share delivery to a specific area. However, the ES does not indicate which product orders are to be removed from one truck to another to balance the workload of the drivers. Such an adjustment relies on the drivers' knowledge and experience.

A final limitation is that the items included in the questionnaires for cost-benefit predictions reflect the authors' views and biases. There is no claim here that the items listed are the only ones that could be included or that some of the items given could not be excluded. Other researchers might have stated the same items differently or have generated different items entirely, depending on the nature of the problems studied.

Recommendations

The prediction of whether or not the trucks will be overloaded relies on the judgment of the division manager and the drivers. Such a decision is made in a limited time based on limited information. For the prediction to be more accurate, supplementary research is required to cast more light on the intuitively important roles of other factors of a qualitative nature that affect the working time of the drivers. These factors might include the time of day (e.g., morning, afternoon) that customers expect delivery, the relationships between the drivers and the customers, the attitudes of the drivers toward the task, etc.

Training programs in managing end-user attitudes and expectations from an ES should be an important topic for ES project managers to address. Improvement may call for changes in practices currently used in industry since training for ES end-users has been found to be lacking in most organizations (Wells & Guimaraes, 1992).

Conclusions

This paper has contributed to a better understanding of the development and application of ES for improving the productivity of organizations. The study presented an attempt to build regression models that would predict the working time of each driver for a pharmaceutical distributor and to develop a KBS by acquiring the knowledge and experience from the division manager and the drivers. The proposed ES, a combination of a KBS and regression analysis, will serve as a complement of the existing system for the company that will allow the trucks to be used more efficiently, will minimize overtime costs, will balance the workload of the drivers, will reduce transportation costs, will increase the capabilities of handling more orders, will improve productivity, and will ensure decision consistency. The proposed ES can be used by the division manager, the drivers, or any potential user as a knowledgeable assistant to improve the capabilities of solving delivery problems. However, an ES cannot replace humans because many ideas, knowledge, and intuition are difficult to include in one system. Thus, some decisions may rely on the judgment of the manager and the drivers.

In addition, this paper presented some methods and forms for making rational decisions as to whether or not the proposed project will be successful. The validity of the project is determined by comparing the costs with anticipated benefits. This comparison is termed a cost-benefit analysis. The perceived benefits include cost savings of not increasing labor and equipment, and cost reductions from improving productivity. However, learning, development, implementation, maintenance, and opportunity costs associated with the ES must also be considered. One of the best ways to spread the costs and to leverage the benefits received is to blend the ES with other programming, thereby enhancing the capabilities of both systems. The case study shows both the feasibility and cost-effectiveness of the proposed ES.

After the justification process, management must act quickly. A rapid and smooth transition from problem identification and solution justification to actual solution implementation is imperative. The case study presented in this paper is a good illustration of the development and application of ES not only for distribution systems but also for other types of operation.

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