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Application of Expert Systems to the Evaluation of Managerial Performance in Public Enterprises of Developing Countries

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One of the most difficult problems encountered in the performance evaluation of public enterprise managers is the development of a mathematical representation of performance which includes their social, economic and financial objectives. This paper examines the performance function trade-off between increasing the number of criteria and the level of difficulty in the assignment of subjective weights for each criteria and postulates the use of expert systems to eliminate the trade-off. It presents the results of an experiment designed to test the applicability of expert systems to performance evaluation using an expert system shell to replicate the enterprise classification performed by the Pakistani Evaluation System. On the basis of a successful replication, the paper suggests a methodology to evaluate public enterprise managers without the requirement of developing explicit mathematical representations of performance.

INTRODUCTION

THE CURRENT INTEREST in the performance of public enterprises, arising mostly from the reform, restructuring and privatization issues, has highlighted the importance of control systems for public enterprises at the government level and in particular of one of their subsystems: the evaluation of managerial performance.

Managerial performance is difficult to evaluate due to the necessity that performance measures cover not only the achievement of financial, but also of economic and social objectives of public enterprises. These are often qualitative and do not lend themselves to mathematical formulations.

The difficulties in the design of performance measures that incorporate multiple objectives are magnified by traditional automatic data processing requirements since they include the definition of explicit mathematical formulas to develop the corresponding machine-oriented algorithms.

In order to express performance with a single mathematical formula, most designers have attempted to reduce the number of criteria variables in the performance functions, neglecting in the process qualitative indicators that normally represent social performance and other important quantitative indicators. Furthermore, the implicit assumption that the performance of an enterprise can be represented by an additive function of performance variables and their weights has been questioned and refuted by experts in the field.

The Signalling System established by the Ministry of Production in Pakistan to evaluate managerial performance in approximately 50 enterprises under its purview is an interesting example of the designers' dilemma. In order to have a system that would be easily understood by government officials and managers, they designed a simple formula which aggregates in one index target achievements in financial profitability, labour productivity and physical production, ignoring other financial, economic and social criteria.

The designers of the Signalling System are aware of the necessity to add other performance criteria to their formula but they found that defining the mathematical weights for each factor becomes increasingly difficult as the number of factors increases.

In order to help overcome the single mathematical function bottleneck to the design of evaluation systems, the International Center for Public Enterprises has been researching the feasibility of utilizing non-traditional, computer support systems for the solution to this difficult problem.

The research effort studied the possible utilization of artificial intelligence computer technology, particularly the application of expert systems since they are well suited for application in situations where knowledge is only partly formalized and where qualitative indicators as well as incomplete, inconsistent and uncertain data need to be incorporated.

In order to investigate the feasibility of application of expert systems to the problem of performance evaluation, an experiment was performed to replicate the evalution scheme developed in Pakistan without the use of the evaluation formula or of the assigned weights.

The experiment was based on the application of an expert system shell—ASSISTANT 86—to automatically construct a set of decision rules in order to evaluate enterprises' "learning" from the examples provided by the Pakistani Signalling System.

The principal objective of this paper is to present the results of this experiment as a first positive step in the utilisation of expert systems to support the performance evaluation process.

An implied assumption of the experiment is that the replication of a relatively simple quantitative evaluation procedure will give evidence of the system's usefulness in supporting more complex quantitative-cum-qualitative evaluation procedures.

To test the capability of "ASSISTANT 86" to replicate the evaluation methodology of the Pakistani evaluation system a data set corresponding to 55 enterprises for the year 1984–1985 was divided into learning and testing subsets. The knowledge was built into the expert system utilising the examples in the learning subset and then the enterprises of the testing set were evaluated by "ASSISTANT 86".

The enterprise classification utilising "ASSISTANT 86" matched the Pakistani classification in 14 out of the 15 test cases. This successful replication of the Pakistani evaluation scheme without the utilisation of an explicit mathematical representation gives the foundation for the design of a general methodology to evaluate enterprises utilising examples of human expert evaluations as a source of the computer knowledge base and the replication by the computer of the expert's logic for the evaluation of a large number of enterprises.

The strength of the application of expert systems to support the performance evaluation process resides in the fact that these systems, unlike conventional computer support systems based on classical algorithmic approaches, encode human experience and judgement, logical reasoning, conclusions and assessment that allow the user to interact not only with the computer output, but with the internal logical reasoning itself in order to obtain a transparent interpretation of results.

PERFORMANCE EVALUATION SYSTEMS FOR PUBLIC ENTERPRISES

The application of principles of management control to public enterprises requires the establishment of a government control unit (focal point) which will consider all public enterprises under its control either as profit or cost centres and establish a set of criteria to evaluate the performance of enterprise managers so that incentive packages can be offered based on individual unit performance.

Although the principle is quite simple, the design and development phases of the system are fraught with difficulties, among them: the establishment of performance criteria measurements which will take into account the dual nature of public enterprises, i.e. their public and enterprise dimensions; the definition of control standards to permit comparison of performance, the availability of comparable information from the different units and particularly the definition of an integrated measure of performance.

The evaluation systems of South Korea [17] and Pakistan [14] use negotiated subjective weights to aggregate evaluation criteria. One of the principal problems in the design of these aggregate indices is the trade-off between the number of criteria used and the difficulties in defining the weights. Aware of this fact, most designers have minimized the number of criteria used neglecting in the process important financial aspects such as liquidity and solvency and socio-economic ones such as contributions to employment and foreign exchange generation, etc.

Furthermore, the implicit assumption that a single additive function represents performance is questioned by many experts in the field since it is argued that performance can best be assessed as a multiple tier process with the results at each level depending on the previous one; for example it has been pointed out that in a private corporation return on capital employed (ROCE) is critical if, and only if, the enterprise has a positive cash flow and ROCE is greater than or equal to its cost of capital, thus the assessment at each stage depends on previous conditions.

The problem with stepwise comprehensive evaluations is that they are time-consuming and for a large number of enterprises they would either require a large number of evaluators to accomplish or the task cannot be accomplished. This is the case of the Office of the Comptroller in Pakistan, which undertakes such an effort; with a small staff, they evaluate only ten out of 200 enterprises a year.

It is this trade-off between comprehensive evaluation and the need to evaluate a large number of enterprises that prompted ICPE to investigate the possible utilisation of expert systems to help break the trade-off; in other words, to design support systems that would allow government officials to reproduce the evaluation logic of recognized experts in the field to evaluate a large number of enterprises as a replacement for the traditional utilization of mathematical formulas to represent the problem.

Since the Pakistani signalling system has been in operation for the last five years and data is available, its evaluation results are utilised in this exercise in order to test the applicability of expert systems to the performance evaluation process.

THE SIGNALLING SYSTEM

The Signalling System set up by the Experts Advisory Cell (EAC) of the Ministry of Production of Pakistan in 1983 is based on a simple institutional principle [1, 13]. The EAC is the control unit (focal point) and its main functions are: to establish tentative profitability and productivity targets for about 50 manufacturing enterprises; to negotiate and formalise these targets and related grading mechanisms with the CEOs by means of formal contracts; to evaluate management's performance with respect to the contract and to award incentive bonus payments as functions of performance.

The core of the system is the mechanism for target-setting. For each evaluation criterion, profitability, labour productivity, and physical production, a five-interval target spectrum is defined. If the actual performance is in the highest interval, the enterprise receives a grade of 5, 4 for the second interval and so forth. The grades obtained for each criterion are averaged using previously negotiated weights. Based on the weighted score enterprises are classified from A to E. If an enterprise is classified as Grade A, a three-month salary bonus is paid to all managers, B graded manager receive two months, those graded C and D one and one-half respectively and Grade E managers receive no bonus at all.

ARTIFICIAL INTELLIGENCE METHODS APPLIED TO MANAGERIAL PROBLEMS

The application of artificial intelligence (AI) methods to the solution of managerial problems began in 1980 and a number of successful simple and powerful prototypes have been developed [6, 7, 8].

One of the most promising AI applications, for unstructured problems such as the performance evaluation of public enterprises, is based on the methodology of "expert systems" and specifically in the techniques developed for automatic knowledge acquisition.

These methods, techniques and tools enable the management analyst to deal with domains where knowledge is not well formalised, where data is often incomplete, inconsistent and uncertain and where it is also important to use qualitative attributes that influence decisions.

Decision support systems built using artificial intelligence methods are extremely user-friendly, providing the management analyst with support for his logical reasoning and conclusions, and in the interpretation of results.

EXPERT SYSTEMS AND AUTOMATIC KNOWLEDGE ACQUISITION

Expert systems [5, 9, 12] are computer programs implemented with different artificial intelligence methods which use specialised knowledge about a particular problem domain, and logical reasoning based on symbolic and often qualitative data, the aim being to perform at the level of the best human experts in the particular field.

An expert system typically consists of a knowledge base, an inference engine and a communication module. The knowledge base contains the human expert's specific knowledge (domain knowledge) for the desired application. The inference engine consists of a set of algorithms and reasoning methods that interact with the knowledge base in order to solve particular problems and answer users' queries. The communication module links the system with the user in a user-friendly way, allowing the user to interact with the internal logic of the system.

AUTOMATIC KNOWLEDGE ACQUISITION

Usually, the most critical problem in the application of expert systems is extracting the domain-specific knowledge from experts or from the literature and formulating it in the form of rules. This method is expensive and time-consuming [15] as it requires the intense engagement of the application domain expert over a long period of time. This situation is further complicated since it appears that experts who are very capable in the application of their knowledge are often unable to formulate it explicitly in the systematic, correct and comprehensive manner required for computer applications.

It is already widely acknowledged that machine learning tools can be used to overcome the problem of expert system knowledge acquisition. In this paradigm the rules do not have to be extracted from expert's reasoning. Human experts are only required to interpret domain specific data or to specify enough typical examples and/or counter examples.

Machine learning systems such as "ASSISTANT" and its latest version "ASSISTANT 86" [4] permit automatic construction of decision rules from examples of expert decisions. In "ASSISTANT 86" knowledge acquisition is based on learning from examples. The result of learning is a classification rule in the form of a decision tree, which can be used to classify new objects. The structure of the system is shown in Fig. 1.

The method is based on Quinlan's ID3 program [16] with several improvements added to the original algorithm [2]. These additions permit the utilisation of continuous attributes, besides discrete ones as in ID3, and of unreliable and incomplete information. The improvements

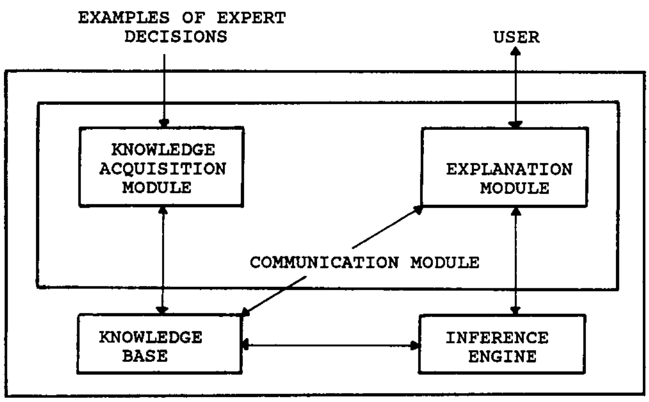

Fig. 1. Structure of an expert system built by "ASSISTANT 86".

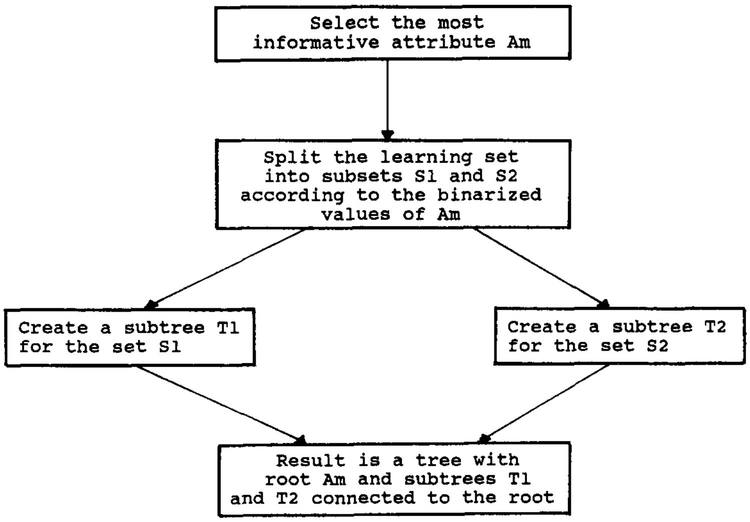

Fig. 2. A flowchart of the basic algorithm of "ASSISTANT 86".

enable the system to automatically detect and reject inconsistencies and exceptions in the learning data, to help improve the structure and to control the size and shape of decision trees, and to facilitate the clustering of attributes and decision classes [3].

"ASSISTANT 86" has been applied to a number of practical problems in medical diagnosis and prognosis [10] and it has also been successfully used to generate automatically a knowledge base for a steel classification expert system used in a large Yugoslav steel plant [11].

The application of "ASSISTANT 86" requires an appropriate set of learning examples with known decision classes. The result is presented in the form of a classification tree which can be used either as a consultant for decision making or as a new form to present the knowledge.

The classification tree obtained as a result of inductive learning by "ASSISTANT 86" is composed of internal nodes, branches and leaves which correspond to attributes, attribute values and classes respectively. During the tree generation, "ASSISTANT 86" selects the most informative attribute as the root of the tree, splits the learning set into subsets according to the values in the branches, and recursively creates subtrees for every subset. The criterion for selecting the most informative attribute is the entropy measure [4]. If all learning examples in the node belong to the same class the tree construction is stopped and the leaf (a node with no successors) is labelled with the given class. A flow-chart of the basic algorithm is shown in Fig. 2.

REPRODUCING EXPERT KNOWLEDGE BY "ASSISTANT 86"

An experiment was designed to test the capability of "ASSISTANT 86" to reproduce expert knowledge in the public enterprise evaluation domain. The objective of this experiment was to investigate the applicability of expert systems to support the design of enterprise evaluation methodologies without the requirement of a precise mathematical formulation to measure performance.

The experiment was based on the reproduction of the enterprise classification performed by the Experts Advisory Cell (EAC) of the Ministry of Production of Pakistan with data for the 1984–1985 evaluation exercise. The main underlying hypothesis was that a necessary condition (although not a sufficient one) for the utilisation of expert systems was their ability to reproduce a simple classification scheme where the results were known.

The task of the expert system was to automatically construct the knowledge base utilising a set of learning examples provided by the EAC and to classify each enterprise of the test set into one of the five classes (categories) A through E—excellent to poor—on the basis of three

PROFITABILITY			PRODUCTION			PRODUCTIVITY			ENTERPRISE CLASSIFICATION
Max.	Min.	Actual	Maximum	Minimum	Actual	Max.	Min.	Actual	
4.73	2.13	3.02	0.00	0.00	0.00	0.89	0.76	0.89	C
19.20	15.32	17.64	0.00	0.00	0.00	1.12	0.92	1.01	B
2.38	0.98	1.47	0.00	0.00	0.00	1.01	0.82	0.82	D
7.47	4.08	7.47	22000.00	20000.00	20000.00	1.11	0.91	1.11	A
8.18	6.09	7.49	505000.00	450000.00	498131.00	1.04	0.86	0.86	B

Fig. 3. A sample of five enterprises, taken from the learning data subset.

attributes (performance criteria): profitability, productivity, and physical production.

The data set corresponds to 55 industrial enterprises classified for a particular year using the EAC's weighted formula previously described. The data set was divided into two subsets: the learning set, consisting of 40 enterprises, chosen at random, and the testing set, consisting of the remaining 15 enterprises.

The learning subset format is presented in Fig. 3. For each of the three evaluation criteria or attributes, profitability (PR), physical production (PP) and productivity (PDT), there are three values: maximum (MAX), minimum (MIN) and actual. The maximum and the minimum values represent the negotiated target range values for each enterprise, and the "actual" corresponds to the actual value for that particular year presented as percentages, and output units index values respectively.

The Signalling System segments the target range of attributes into five categories, but this information was purposely not included in the data in order to let "ASSISTANT 86" select the appropriate boundary values.

The target ranges of actual attribute values are not identical for all enterprises, thus a linear transformation is utilised in order to normalise the actual attribute values for different enterprises. A normalised value for each attribute within the learning example is computed according to the following formula:

$$\text{Normalised Value} = \frac{\text{ActValue—MinValue}}{\text{MaxValue—MinValue}}$$

For enterprises which do not include physical production as a performance criterion the attribute physical production is given a value of -1 to allow the computer to identify an empty cell. Figure 3 depicts the normalised dataset for the sample of enterprises presented in Fig. 4.

To determine the appropriate subinterval boundary values for the attributes, each interval (0, 1) is split into ten equidistant subintervals. These subintervals are tested to determine if their range includes a sufficient number of actual values from the learning dataset. If an empty interval is found it is split in half and then each half is fused to its neighbouring interval. For example, in the case where no learning examples have actual values of an attribute in the interval (0.2, 0.3), i.e. if the interval is empty, it is eliminated and only the subintervals (0.1, 0.25) and (0.25, 0.4) remain.

After the subintervals are determined, "ASSISTANT 86" is used to generate the enterprise classification tree with the 40-enterprise learning data set. The output shown in Fig. 5 indicates that profitability, depicted as the root of the tree, is the most informative attribute. The branches from the root node correspond to the split of the attribute's values: if the value of

Profitability	Physical Production	Productivity	Enterprise Classification
0.34	-1.00	1.00	3
0.60	-1.00	0.45	2
0.35	-1.00	0.00	4
1.00	0.00	1.00	1
0.67	0.88	0.00	2

Fig. 4. Normalised data for a sample of five enterprises.

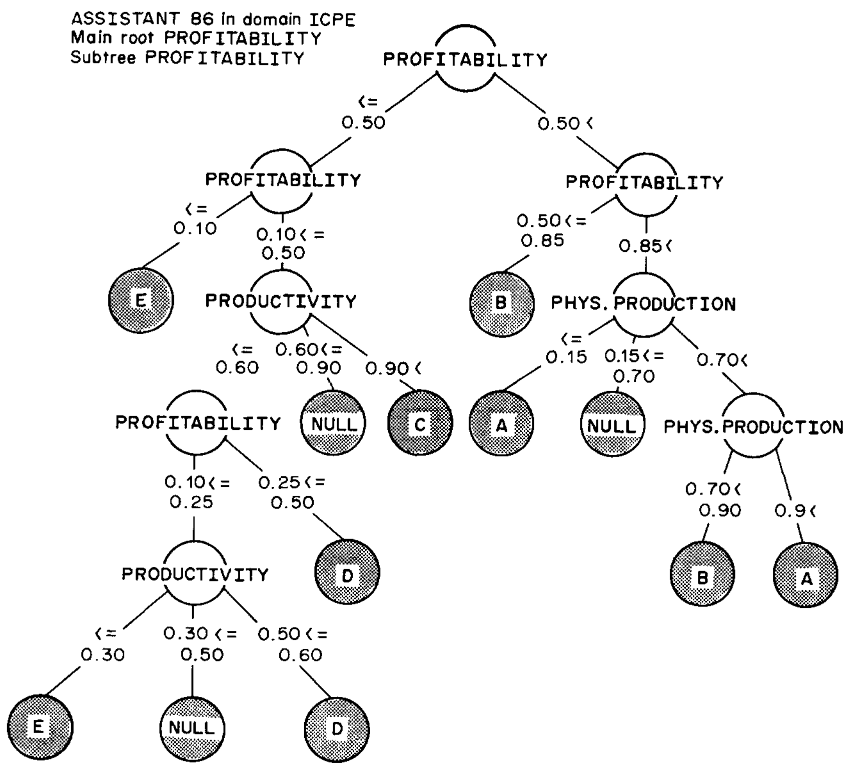

Fig. 5. Classification for Performance Evaluation tree constructed with "ASSISTANT 86".

PROFITABILITY is less than or equal to 0.50 (normalized), then that instance falls in the left subtree, otherwise it falls into the right subtree, in this manner this tree can be used to classify new instances with unknown classes.

Knowledge presented in the form of a classification tree appears to be more understandable than rules because of its graphic represention. However, the usual way of knowledge representation in expert systems is in the form of "if-then" rules. This set of rules provides information which is equivalent to that previously presented in the classification tree.

Utilising the "ASSISTANT 86"-generated classification tree, the test sample of 15 enterprises was classified and the results compared with the EAC classification. The results of the classification using "ASSISTANT 86" and the EAC classification, as shown in Fig. 7, only differ in one instance out of fifteen.

The classification tree constructed by "ASSISTANT 86" proves that the Signalling System relies heavily on financial profitability in the classification of the enterprises. Thus if the value of the profitability index is greater than 85% of the target range, this is a necessary

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If PROFITABILITY ≤ 0.10) or
   (1.10 < PROFITABILITY ≤ 0.25) and (PRODUCTIVITY ≤ 0.30) then Class E.

If (0.10 < PROFITABILITY ≤ 0.25) and (0.50 < PRODUCTIVITY ≤ 0.60) or
   (0.25 < PROFITABILITY ≤ 0.50) and (PRODUCTIVITY ≤ 0.60) then Class D.

If (0.10 < PROFITABILITY ≤ 0.50) and (PRODUCTIVITY > 0.90) then Class C.

If (0.50 < PROFITABILITY ≤ 0.85) or
   (PROFITABILITY > 0.85) and (0.70 < PHYS. PRODUCTION ≤ 0.90) then Class B.

If (PROFITABILITY > 0.85) and (PHYS. PRODUCTION ≤ 0.15) or
   (PROFITABILITY > 0.85) and (PHYS. PRODUCTION > 0.90) then Class A.
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Fig. 6. Set of "if–then" rules derived for "ASSISTANT 86" decision tree.

Profitability	Physical Production	Productivity	EAC Classification	ASSISTANT 86 Classification
0.00	0.12	0.89	E	E +
0.00	-1.00	0.00	E	E +
0.26	-1.00	0.05	C	D -
1.00	-1.00	0.45	A	A +
0.00	-1.00	0.00	E	E +
1.00	-1.00	0.58	A	A +
0.84	-1.00	0.15	B	B +
0.00	0.00	0.00	E	E +
1.00	0.05	0.56	A	A +
0.00	0.00	0.21	E	E +
1.00	0.63	0.68	B	B +
0.00	-1.00	0.00	E	E +
0.00	-1.00	0.00	E	E +
1.00	-1.00	0.00	A	A +
0.00	-1.00	0.00	E	E +
			15	14 *

Note: + sign indicates matching classification
* this figure represents the number of matched pairs

Fig. 7. Enterprise classification, EAC and "ASSISTANT 86".

condition for the enterprise to be classified in Class A, and a profitability index of less than 0.10 is a sufficient condition for the enterprise to be classified in Class E.

The discrimination among classes B, C and D takes productivity and physical production indices into account to different degrees; thus with a level of profitability index between 0.25 and 0.50, if productivity is greater than 0.9, the enterprise belongs to Class C, but if this index is less than 0.6, then the enterprise is classified as D. Where the productivity index is between 0.6 and 0.9, "ASSISTANT 86" assigns it a null leaf meaning that the learning set does not provide enough information for classification within this interval.

The classification tree reflects the logical ordering of the Signalling System classification scheme: one exception to this regularity is the A leaf corresponding to the profitability index whose value is greater than 0.85 and the physical production index is less than 0.15. This rule implies that an enterprise may be classified in Class A having low achievement of the physical production target which calls for further investigation. Analysing the raw data it appears that this particular enterprise reached high levels of target achievment in both profitability and productivity and did very poorly in the attainment of its physical production target. This can be interpreted as an inconsistency in the target-setting process.

CONCLUSIONS

In order to test the applicability of expert systems to support public enterprise performance evaluation processes, a successful experiment was made to replicate the simple algorithm used by Pakistan's EAC. The experiment shows not only that this knowledge can be accurately reproduced but it also provides a new insight into knowledge of enterprise performance evaluation. The generated classification tree provides the analyst with a compact and easily understandable representation of the classification knowledge that also enables the analyst to trace irregularities and inconsistencies in the evaluation process itself.

The goal of this experiment was not to develop a practical enterprise performance evaluation expert system but to test whether the proposed methodology and tools were suitable to be chosen as a basis for developing a complex enterprise performance evaluation system including substantially more decision parameters, quantitative and qualitative, than the EAC evaluation scheme.

The successful replication of the EAC enterprise classification results by "ASSISTANT 86" is the first required step to proceed with the research to develop and test comprehensive evaluation methodologies that will not be dependent on the formulation of a unique mathematical algorithm to measure performance.

Based on these results, the next research step should be to develop and test an evaluation methodology in accordance with the following phases:

Phase 1—Data gathering.
Phase 2—Building the knowledge base with "ASSISTANT 86".
Phase 3—Evaluation of enterprises and analysis of results.

Phase 1—Data gathering

Most developing countries have specialised units that act as government focal points to supervise public enterprises and one of their principal functions is to develop computerised management information systems. Using this information, these units would calculate standard financial and economic indicators for public enterprises and undertake a sample survey to obtain information on the attainment of social and other qualitative objectives for each enterprise.

Phase 2—Building the knowledge base

An expert group meeting with the country's top enterprise evaluators and some specialised foreign experts, e.g. finance banking experts, loan appraisers, etc., should be convened to evaluate by consensus a sample of 20 to 30 enterprises for a period of one week, using the data prepared by the focal point government unit. The results of this evaluation (the learning subset) would be fed into a computer with the capability of a Micro PC-AT to build the knowledge base using "ASSISTANT 86" software.

Phase 3—Evaluating enterprises with "ASSISTANT 86" and analysis of results

The inference engine will then evaluate the rest of the enterprises and the expert group should analyse the results on a sample basis to validate the computer results.

After the evaluation process is undertaken, the specialised unit could replicate the evaluation process whenever necessary for all public enterprises.

This proposed methodology is applicable in developing countries where the number of enterprises is large (over 100) and where a basic management information system is in operation. The computer requirements are minimal and local staff can be trained to run and maintain the expert system software in two to three weeks. The costs are concentrated on the one week expert meeting and the most important characteristic of this methodology is that it does not require continuous dependency on foreign consultants. They are replaced by expert system computer consultants.

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