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Theory and Methodology

Evaluating sampling strategy under two criteria

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Abstract

This paper integrates elements of Information Economics, Quality Control, Portfolio Selection and Decision Theory into an approach to facilitate the selection of an attribute sampling plan for a lot subject to inspection. The optimal selection is based on two criteria: the expected payoff and its standard deviation. Quality sampling plans are introduced as information structures, and ranked by the two criteria. The paper shows that different organizations should prefer different plans according to their strategies and preferences. The paper provides methods to rank order different sampling plans by an economical criterion as opposed to the commonly accepted pure statistical criterion.

Keywords: Information economics; Information structures model; Information evaluation; Quality management; Statistical quality control; Sampling plan

1. Introduction

This paper develops a normative method for selecting an optimal sampling plan for a given inspection lot based on the integration of elements in Information Economics, Statistical Quality Control, Financial Theory of Portfolio Selection and Decision Theory. While all these elements have been well defined and proved separately in the literature, this paper presents a full-scale real-life example of the integration of the methods.

The Information Economic approach to evaluate the value of information is commonly based on the Information Structures model developed by Marshak (1971) McGuire and Radner (1986). The approach to information evaluation is based on quantitative analysis of situations in which the information system (IS) can be rigorously modeled and the impact of various traits of information on the decision maker's performance can be calculated.

The starting point for evaluation is a set of assumptions (axioms) about the decision maker's behavior and preference function. Under these assumptions, an information system is rigorously modeled such that the payoffs to the decision maker can be computed for various alternative sets of information that can be examined.

The model formulates an IS as a stochastic matrix of conditional probabilities that transforms events into signals. The decision maker (DM) selects the optimal action under given (discovered from past experience) values of a-priori probabilities of states of nature, and given values of payoffs. The model uses the expected payoff in monetary values or utility units as a criterion for decision making. Since the information structures model is the cornerstone to the analysis performed in this paper, we shall elaborate on it in the next section.

Based on the finance theoretical approach to risk (see, for example, Copeland and Weston, 1988), the information structures model was enhanced by Ahituv and Spector 1990 to enable decision makers to choose an information system under two criteria: the expected payoff, and the standard deviation of the distribution of payoffs around the expected value gained from an information structure. We will refer to the information systems ranking according to these two criteria as the bi-attribute rank ordering.

The literature contains but few applications of information economics modeling, and information structures modeling in particular. Stohr (1979) uses the information economics approach for observing inventory levels in an optimal way. Examples of quality control problems using the information structures model have been demonstrated by Demski (1972). Ronen (1994) built a full methodology showing quality control attribute sampling as a special case of the information structures model.

Bi-attribute rank ordering is widely used in business. A major goal of any profit organization is to reduce variability and, at the same time, to increase the expected value of its payoff (or profit). This approach is accepted in the finance as well as in production theories (see, for example, Copeland and Weston, 1988, and Deming, 1986). In the production area, the notion of the contribution of an information system to increasing the expected value of the organization's profit is well known. Much less emphasis has been devoted, however, to the effect of an information system on reducing variability of processes or to the selection of such a system to meet the desired mean-variation requirement. In the production area we often find two opposing trends: one trend is to reduce variability, as presented by Deming (1986) and JIT adherents (Schonberger, 1986). The other is to protect the market or critical resources against variability (for example, see Goldratt and Fox, 1986).

This paper applies the information structures bi-attribute rank ordering methodology for quality attribute sampling, and rank orders quality plans in a different order than previously done. The paper introduces a methodology of choosing a preferred plan under given risk aversion of the decision makers.

The next section briefly reviews the information structures model. Section 3 centers on risk measurement and methods of information evaluation integrating risk and expected payoff together. Section 4 shows how sampling can be represented in the information structures model. The mean variance graph methodology for selecting an optimal sampling program is presented in Section 5. The last section provides some concluding remarks.

2. The information structures model: A review

As this review will be brief, the reader is referred to McGuire (1986) for a more detailed description.

Let $\boldsymbol{E}$ be a finite set of events, $\boldsymbol{E} = \{e_1, \dots, e_{\mathrm{Ne}}\}$. Let $\boldsymbol{p}$ be a vector of a priori probabilities associated with the events in $\boldsymbol{E}$, $\boldsymbol{p}^{\mathrm{t}} = (p_1, \dots, p_{\mathrm{Ne}})$, where $\Sigma p_i = 1$ and $p_i \geq 0$. [1]

Let $\boldsymbol{Z}$ be a finite set of signals, $\boldsymbol{Z} = \{z_1, \dots, z_{\mathrm{nZ}}\}$. An information structure $\boldsymbol{Q}$ is defined as a stochastic matrix $(\mathrm{Ne} \cdot \mathrm{nZ})$ of conditional probabilities, under which signals of the set $\boldsymbol{Z}$ will be displayed at the

[1] The superscript t stands for a transpose operator.

occurrence of an event of $\boldsymbol{E}$. Thus the element q_{ij} of the matrix $\boldsymbol{Q}$ is the probability that for a given event e_i, signal z_j will be transmitted.

Let $\boldsymbol{A}$, $\boldsymbol{A} = \{a_1, \ldots, a_{nA}\}$ be a finite set of actions that can be taken by the decision maker. Let $\boldsymbol{U}$ be an (nA · nE) matrix, each of its element u_{ij} reflects the payoff gained by the DM when an action a_i is taken while event e_j occurs.

The DM cannot observe the events but only the signals, and chooses actions accordingly. The DM's strategy is delineated by an (nZ · nA) stochastic matrix $\boldsymbol{D}$. Each element d_{ij} of $\boldsymbol{D}$ determines the probability that action a_j will be taken upon observation of signal z_i. The model's assumption is that the DM *optimizes* $\boldsymbol{D}$ to obtain the maximum expected payoff.

Let $\boldsymbol{\pi}$ be a square matrix containing the vector $\boldsymbol{p}$ in its main diagonal and zeros elsewhere. The expected payoff gained from $\boldsymbol{Q}$, $\boldsymbol{U}$ and $\boldsymbol{D}$ is given by $\mathrm{tr}(\boldsymbol{QDU\pi})$, where 'tr' stands for the trace operator. Maximization of the above is obtained by solving a linear programming problem for the elements of $\boldsymbol{D}$ constrained by the properties of a stochastic matrix. Let us define $F(\boldsymbol{Q}, \boldsymbol{U}, \boldsymbol{\pi}) = \max_D\{\mathrm{tr}(\boldsymbol{QDU\pi})\}$ (Ahituv and Wand, 1984; McGuire and Radner, 1986).

Given two ISs $\boldsymbol{Q}$ and $\boldsymbol{R}$ operating on the same set of events $\boldsymbol{E}$, $\boldsymbol{Q}$ is defined to be *generally more informative than* $\boldsymbol{R}$ if the maximal expected payoff yielded by $\boldsymbol{R}$ is not larger than that yielded by $\boldsymbol{Q}$ for all payoff matrices $\boldsymbol{U}$ and all probability vectors $\boldsymbol{p}$. A *partial* rank ordering on the set of ISs is provided by the Blackwell Theorem (Marschak, 1971; Radner, 1986) which states that $\boldsymbol{Q}$ is *generally more informative* than $\boldsymbol{R}$ if and only if there exists a stochastic (Markov) matrix $\boldsymbol{M}$ with appropriate dimensions such that $\boldsymbol{Q} \cdot \boldsymbol{M} = \boldsymbol{R}$; $\boldsymbol{M}$ is called the garbling matrix. A *complete* rank ordering of ISs is provided for each given pair of payoff matrix $\boldsymbol{U}$ and probability vector $\boldsymbol{p}$. $\boldsymbol{Q}$ is more informative than $\boldsymbol{R}$ for a given $\boldsymbol{U}$ and $\boldsymbol{p}$ if $F(\boldsymbol{Q}, \boldsymbol{U}, \boldsymbol{\pi}) > F(\boldsymbol{R}, \boldsymbol{U}, \boldsymbol{\pi})$ (Radner, 1986).

3. The variance of the value of information

Based on the finance theoretical approach to risk (e.g., Copeland and Weston, 1988), we develop a model reflecting the distribution of payoffs around the expected payoff gained from an information structure $\boldsymbol{Q}$, a decision rule $\boldsymbol{D}$, a payoff matrix $\boldsymbol{U}$, and a vector of a-priori probabilities $\boldsymbol{p}$ (or its matrix equivalent $\boldsymbol{\pi}$) (Ahituv and Spector, 1990).

Definition 1 (Variance of IS). Let $\boldsymbol{Q}$, $\boldsymbol{D}$, $\boldsymbol{U}$, $\boldsymbol{\pi}$ be an information structure, a corresponding decision rule, a payoff matrix and a matrix of a-priori probabilities (respectively). Let us define matrix $\boldsymbol{\Delta U}$ (dimension a · e) as a matrix whose elements Δu_{ij} are defined as follows:

$$\Delta \boldsymbol{u}_{ij} = \left[\boldsymbol{u}_{ij} - \mathrm{tr}(\boldsymbol{QDU\pi})\right]^2.$$

Hence, the variance of the information value ($\mathrm{Var}(\boldsymbol{QDU\pi})$) is defined as follows:

$$\mathrm{Var}(\boldsymbol{QDU\pi}) - \mathrm{tr}(\boldsymbol{QD\Delta U\pi}).$$

It is worth noting that the traditional expected payoff measurement does not provide any indication about the distribution of the payoffs, thus it does not include any information about payoff diversity. The proposed measurement does, however, indicate the distribution of the payoffs; hence the decision maker who has to select an information structure may account for payoff variations as well (for more details the reader is referred to Ahituv and Spector, 1990).

It should be noted that for any expected-payoff-maximization problem there is always at least one optimal solution which generates a 'pure' decision rule (zero–one matrix) (see McGuire, 1986, p. 103). A number of optimal solutions will be available if and only if the objective function is 'parallel' to the hyperplan defining the constraints. For the minimize-variance problem the same minimum value of a quadratic function will occur a number of time only when there is a number of local optimum points. Hence, the decision rules can be modified to a general approach where the evaluator wishes to select the system minimizing the variance subject to a constraint imposing on expected payoff, or to select a system maximizing expected payoff subject to a constraint imposed on the variance. The approach presented here may be modified and adapted for such cases as well (see Ahituv and Wand, 1984, and Ahituv and Spector, 1990).

4. Quality control sampling as information structures

We first define some of the important terms in quality sampling, and then incorporate them into the information structures model (for more details the reader is referred to Ronen, 1994).

The basic concept in any inspection process is the sampling plan. A *sampling plan* is a decision rule which specifies how large a sample (n) should be, and the maximum allowable number or percentage (c) of defective in the sample [2]. A plan is therefore specified by (n, c). For example, the plan (50, 3) reads as follows: Select a random sample of 50 units and count the number of defective. If the number of defective is equal to or lower than 3, accept the lot; otherwise reject it. In all stages of sampling (incoming, in-process and final inspection) to 'reject' a lot means to do one or all of the following: start an investigation, stop the process, make some adjustment, scrap the materials, return materials to vendor, etc.

A plan of n units can display $n+1$ different results (signals) which correspond to the possible numbers of defective identified by the inspection, that is, $0, 1, 2, \ldots, n$ defective. Thus, a plan can be regarded as an information structure whose domain is the real quality of a lot (i.e., the percentage of defective), and whose range is a set of $n+1$ signals.

An *information matrix of a sample, $\boldsymbol{M}$*, is an information matrix of an n-size sample, where the number of rows is equal to number of states of nature and the number of columns is equal to the number of signals. Thus $\boldsymbol{M}$ is an $(\mathrm{nE} \cdot n+1)$ matrix as follows:

$$\boldsymbol{M} = \begin{matrix} P_1 \\ \vdots \\ P_{\mathrm{nE}} \end{matrix} \overset{y=0,\, y=1, \ldots,\, y=n}{\begin{pmatrix} & & \\ & m_{ij} & \\ & & \end{pmatrix}},$$

where $m_{ij} = \Pr(y=j-1 \mid P=P_i)$, $i=1,\ldots,\mathrm{nE}$, and $j=1,\ldots,n$.

For convenience, the states of nature are arranged in descending order: $P_1 < P_2 < \cdots < P_{\mathrm{nE}}$.

AQL (Accepted Quality Level) is the quality level of a 'good' lot. It is the percentage of defective that can be considered satisfactory as a process average and represents a level of quality which the producer wants to accept with a high probability of acceptance.

LTPD (Lot Tolerance Percent Defective) is the quality level of a 'defective' lot. It represents a level of quality which the producer does not want to accept.

An *information matrix of a plan* is an $(\mathrm{nE} \cdot 2)$ Markov matrix whose rows represent states of nature P_i, $i=1,\ldots,\mathrm{nE}$ and whose columns are the aggregated signals $y \le c$ and $y > c$ (where c is the acceptance number, $0 \le c \le n$; n is the sample size) is called the information matrix of a QC plan. The elements of an information matrix are:

$$q_{i1} = \Pr(y \le c \mid P=P_i), \qquad q_{i2} = \Pr(y > c \mid P=P_i), \quad i=1,\ldots,\mathrm{nE}.$$

[2] This paper deals with attribute plans, where items are inspected dichotomically, for example, as good or bad, acceptable or not acceptable.

A *decision matrix of a plan (D)* is a $2 \cdot 2$ Markov matrix that associates aggregated signals with decisions. The signals are: $y \leq c$ and $y > c$. The decisions are: 'accept the lot' and 'reject the lot'.

The *payoff matrix* (U) is a ($2 \cdot$ nE) matrix of which each element u_{ki} displays the payoff [3] related to a decision k ('accept' or 'reject') and the occurrence of a state of nature i.

The following real-life example, which will serve us from now on as an on-going illustration, clarifies the terms and definitions given above. The quality manager of a large citrus fruit packaging plant has been looking for a 'good' sampling plan for auditing one of the plant's packaging processes. From the 'historical' data it is known that about 80% of the batches are considered 'good'. A 'good' lot is one having 3% defective or less. A 'defective' lot is one having 8% defective or more. By defects we mean fruits with too low size or weight, fruits with inadequate appearance, etc. He considers the following plans: (32, 2) and (50, 3).

Using our methodology, the a-priori probabilities of these states of nature are $p' = (0.8, 0.2)$, and the payoff (penalty) matrix is

$$U = \begin{array}{r} \\ \text{Accept lot} \\ \text{Reject lot} \end{array} \begin{array}{c} \begin{array}{cc} \text{'good' lot} & \text{'defective' lot} \end{array} \\ \begin{pmatrix} 0 & -1000 \\ -150 & -100 \end{pmatrix} \end{array}.$$

Two QC plans are considered: $A = (32, 2)$ and $B = (50, 3)$.

In order to keep the example simple assume that the testing costs are similar for the two plans, which one is to be preferred? [4]

Let Q_A and Q_B be the information matrices for plans A and B, respectively.

$$Q_A = \begin{array}{r} \\ \text{Event 1 (defects = 3\%)} \\ \text{Event 2 (defects = 8\%)} \end{array} \begin{array}{c} \begin{array}{cc} y \leq 2 & y > 2 \end{array} \\ \begin{pmatrix} 0.929 & 0.071 \\ 0.523 & 0.477 \end{pmatrix} \end{array},$$

$$Q_B = \begin{array}{r} \\ \text{Event 1 (defects = 3\%)} \\ \text{Event 2 (defects = 8\%)} \end{array} \begin{array}{c} \begin{array}{cc} y \leq 3 & y > 3 \end{array} \\ \begin{pmatrix} 0.937 & 0.063 \\ 0.425 & 0.575 \end{pmatrix} \end{array}.$$

If the organization's policy is to maximize the expected payoff (or minimizes the penalties) then the optimal decision rule for Q_A and Q_B turns out to be

$$D_A = \begin{array}{r} \\ y \leq 2 \\ y > 2 \end{array} \begin{array}{c} \begin{array}{cc} \text{Accept} & \text{Reject} \end{array} \\ \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} \end{array}, \quad D_B = \begin{array}{r} \\ y \leq 3 \\ y > 3 \end{array} \begin{array}{c} \begin{array}{cc} \text{Accept} & \text{Reject} \end{array} \\ \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} \end{array},$$

and the expected payoffs (penalties) are

$$\max_D \{\text{tr}(Q_A D U \pi)\} = -122 \quad \text{and} \quad \max_D \{\text{tr}(Q_B D U \pi)\} = -104.$$

It may be seen that under these particular circumstances plan B (represented by Q_B) is more informative than A (represented by Q_A), and, therefore, preferred. Had plan A been in use, the switch-over to plan B would improve performance by $-104 - (-122) = 18$.

[3] The payoffs can be expressed in terms of costs, which are estimated by the decision maker or derived from historical data stored in the information system of the organization. Some corporations which have adopted the 'quality costs' concept are able to construct the payoff matrix instantaneously by extracting data from their data base.

[4] If the sampling costs are different one from the other, then the cost can be subtracted from each u_i in matrix U.

In this section we only considered the expected payoff, in the next two sections we will expand the model to deal with payoffs variation as well.

5. Using the bi-attribute rank ordering of quality sampling information structures

As noted in the introduction, a major goal of any profit organization is to reduce variability and, at the same time, to increase the expected value of its payoff (or profit). In the production area we often find two opposing trends: one trend is to reduce variability, and the other is to protect the market or critical resources against variability. By applying the bi-attribute approach to the selection of an information system ('the plan') we will deal with this important issue.

Let us further develop the citrus fruit packing plant example. The same organization is considering the following plans (which happened to obey AQL = 1.5%), for its quality management process. The quality manager considers the following plans:

$$Q = (32, 2), \text{ equivalent to } \boldsymbol{Q}' = \begin{pmatrix} 0.93 & 0.07 \\ 0.52 & 0.48 \end{pmatrix},$$

$$R = (50, 3), \text{ equivalent to } \boldsymbol{R}' = \begin{pmatrix} 0.94 & 0.06 \\ 0.42 & 0.58 \end{pmatrix},$$

$$S = (80, 4), \text{ equivalent to } \boldsymbol{S}' = \begin{pmatrix} 0.91 & 0.09 \\ 0.22 & 0.78 \end{pmatrix},$$

$$V = (200, 8), \text{ equivalent to } \boldsymbol{V}' = \begin{pmatrix} 0.85 & 0.15 \\ 0.02 & 0.98 \end{pmatrix},$$

$$W = (315, 11), \text{ equivalent to } \boldsymbol{W}' = \begin{pmatrix} 0.76 & 0.24 \\ 0.01 & 0.99 \end{pmatrix}.$$

In order to keep the example simple, we assume that the sampling costs for each plan are the same. Let $\boldsymbol{\pi}$ and $\boldsymbol{U}$ be the same as in the on-going example. Let us also assume that the organization's policy is to maximize the expected short-run profit. This policy will then be reflected in the decision rule which represented by matrix $\boldsymbol{D}$:

$$\boldsymbol{D} = \begin{matrix} & \text{Accept} & \text{Reject} \\ y \le c & 1 & 0 \\ y > c & 0 & 1 \end{matrix} .$$

Calculations of the expected payoff and the standard deviations for the plans yield the results listed in Table 1.

Table 1

Sampling plan	Expected payoff	Standard deviation
Null	−170	284
Perfect IS	−20	40
Q	−122	303
R	−104	275
S	−71	205
V	−41	83
W	−49	75

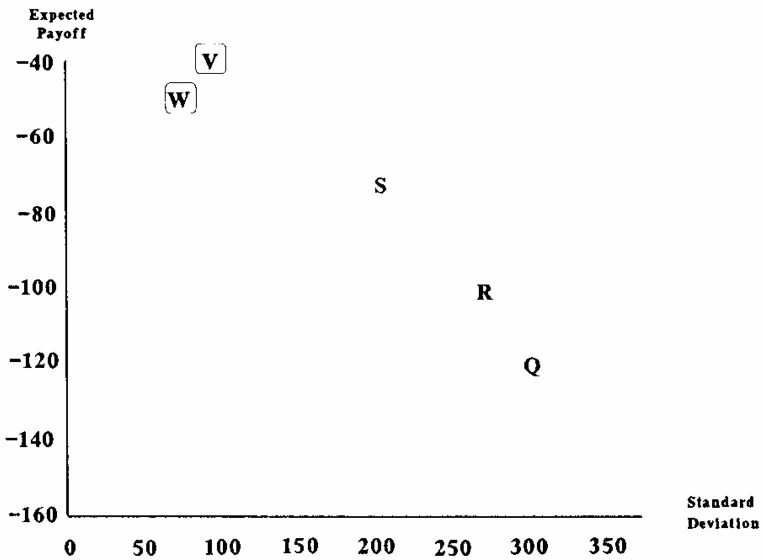

Fig. 1. Efficient frontier diagram. Boxes indicate the efficient frontier set.

The question is: Which plan is preferred by the organization? We will use a two-stage process to answer this question. But first let define the term dominance between two sampling strategies.

Definition 2 (dominance). Let $\boldsymbol{Q}$ and $\boldsymbol{R}$ be two sampling strategies (IS) operating on the same set of events. Let $\boldsymbol{D}_Q$ and $\boldsymbol{D}_R$ be two decision rules for $\boldsymbol{Q}$ and $\boldsymbol{R}$ respectively. $\boldsymbol{Q}$ dominates $\boldsymbol{R}$ for $\boldsymbol{D}_Q$ and $\boldsymbol{D}_R$ if one of the following two conditions is satisfied:

a) $\operatorname{tr}(\boldsymbol{Q}\boldsymbol{D}_Q\boldsymbol{U}\boldsymbol{P}) \geq \operatorname{tr}(\boldsymbol{R}\boldsymbol{D}_R\boldsymbol{U}\boldsymbol{P})$ and $\operatorname{Var}(\boldsymbol{Q}\boldsymbol{D}_Q\boldsymbol{U}\boldsymbol{P}) < \operatorname{Var}(\boldsymbol{R}\boldsymbol{D}_R\boldsymbol{U}\boldsymbol{P})$

or

b) $\operatorname{tr}(\boldsymbol{Q}\boldsymbol{D}_Q\boldsymbol{U}\boldsymbol{P}) > \operatorname{tr}(\boldsymbol{R}\boldsymbol{D}_R\boldsymbol{U}\boldsymbol{P})$ and $\operatorname{Var}(\boldsymbol{Q}\boldsymbol{D}_Q\boldsymbol{U}\boldsymbol{P}) \leq \operatorname{Var}(\boldsymbol{R}\boldsymbol{D}_R\boldsymbol{U}\boldsymbol{P})$.

In the first stage we will reduce the number of feasible candidates by building an efficient frontier, and then we will evaluate the preferred plan by using the mean-var graphical method to evaluate the sampling plan (MESP), which will be presented in the next section. A sampling plan belongs to the efficient frontier group if it is not dominated by any other (considered) plan. Fig. 1 shows the efficient frontier diagram for the information structures (Q, R, S, W, V) for the given payoff matrix $\boldsymbol{U}$ and the a-priori probability vector $\boldsymbol{p}$.

An analysis of Fig. 1 yields that the information structures (IS) representing plans Q, R and S do not belong to the efficient frontier since plan V (and W) is dominating them. In this particular example only plans V and W should be considered since only they belong to the efficient frontier set.

In this section we showed that only partial sampling plans should be considered by the organization, namely those which belongs to the efficient frontier. In the next section we will show how the organization can choose the most appropriate sampling plan out of the efficient frontier.

6. Choosing the right sampling plan by the mean–var graphical method

In this section we will present a method to choose the most appropriate plan for a given family of utility functions, thereby taking into consideration the organization's tendency to reduce variability. Reducing variability is one of the building blocks of today's operations management (see Juran and Gryna, 1980). We will choose the case where the utility is a linear combination of the expected value and variance of payoffs. Although the assumption of linear utility function is quite 'naive' it can be looked upon as a first degree approximation to an arbitrary utility function and it is commonly assumed in management science (Kroll, Levy and Markowitz, 1984). The utility function (or value function) of the decision maker takes the form

$$\text{Value} = \Gamma \cdot E(u) + (1-\Gamma) \cdot \text{SD}(u) \quad \text{where } u \text{ represents the payoff and } \Gamma \in [0, 1].$$

The weight parameter, Γ, represents the relative importance of the two criteria. Γ is determined by the specific variance aversion of the organization. The preferred IS can be selected if the exact value of Γ is known. However, in practice, this value is never known. This problem will be resolved by the graphical method to evaluate sampling plan (MESP).

The MESP method consists of a graph built up of two vertical axes connected by a horizontal axis. The left-hand vertical axis portrays the expected payoff, $E(u)$, in ascending order. The right-hand vertical axis portrays the standard deviation, $\text{SD}(u)$, of the payoffs around the expected payoff in descending order. The horizontal axis portrays Γ-values.

The intersection of the Γ-axis and the $E(u)$-axis represents a relative importance of the expected payoff of 100%, and, naturally, a relative importance of the standard deviation of 0%. Moving to the right along the horizontal axis shows a preference for more importance being attributed to the $\text{SD}(u)$. Hence, at the intersection of the $\text{SD}(u)$-axis and Γ-axis the relative importance of the standard deviation (variance) is 100% and relative importance of the expected payoff is 0%.

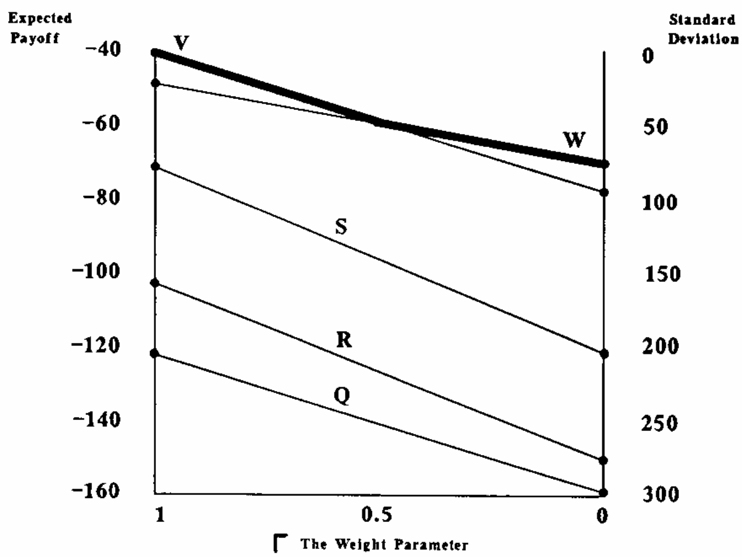

Fig. 2. MESP graph.

For each sampling plan we will draw a line. This line runs between the $E(u)$ and the $SD(u)$ of the sampling plan. In between these two extreme points, lie all the linear combinations of the $E(u)$ and $SD(u)$. The MESP graph of the ongoing example is presented in Fig. 2.

From Fig. 2 we can learn that for any organization, regardless of the level of its variance aversion, only plans V and W should be considered. If the organization is very much concerned with variability (for example, an organization which adopted the TQM methodology) then it will prefer W. If the organization is less concerned about variation (a typical pre-TQM company) it will consider plan V. By applying this method we do not have to know the exact value of Γ, but need only a rough estimate of its value.

7. Conclusions

This paper has incorporated the information economic approach, presented by the information structures model into the managerial theory models of risk management. The subject matter was a real-life problem – the choice of a sampling plan.

Moving toward the information structures concept gives the decision maker the benefit of choosing a sampling plan by an economic criterion, i.e., the expected payoff. Moving towards decision making that involves economic considerations naturally brings us to the bi-attribute approach. Taking into consideration the variance and the mean of the plan, we have shown dominance among sampling plans that have the same AQL, and apparently give the organization the same performance.

The paper has provided a practical tool for choosing the appropriate sampling plan for a given situation: first we transform the potential plans into the information structures model, and then draw the efficient frontier. Inferior plans are thus eliminated immediately. The next step, of drawing the mean variance utility graph, enables the decision maker to choose the right plan that fits his or her preferences. This method reduces the need to assess the exact utility function of the decision maker and thus becomes a practical tool for both researchers and practitioners.

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