A COMPUTERISED APPROACH TO BIDDING STRATEGY IN CIVIL ENGINEERING

by

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A thesis submitted for
the degree of Master of
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SUMMARY

This investigation was concerned with the study of the various aspects of the theory of bidding strategy.

This study was conducted using two methods. The first method is that of analysing actual bidding data by attempting to fit known statistical distributions to them. However, the amount of bidding data available was not enough to draw general conclusions and an alternative method was sought.

The second method is that of computerised simulation using pseudo-random numbers to sample from theoretical distributions. A sub-routine to generate pseudo-random numbers was developed and tested. The influence of important parameters like the number of competitors, the estimation accuracy, the applied mark up and the effect of the job value were studied. A study of the break even mark up was also conducted. The simulation results obtained compare very well with those available in the published literature.

A complete listing of all the computer programs developed is presented together with their flow charts.

BIDDING STRATEGY COMPUTERISED SIMULATION

ACKNOWLEDGEMENTS

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LIST OF SYMBOLS

AM	Arithmetic mean
HM	Harmonic mean
GM	Geometric mean
MD	Mean deviation
μ	Population mean
σ	Population standard deviation
$\bar{x}$	Sample mean
S	Sample standard deviation
X	Random variable
P	Probability
E	Expected value
f(x)	P.d.f., Probability distribution function
F(x)	c.d.f., Cumulative distribution function
V	Variance
Z	Standard deviate
S_e	Standard error of the estimate
e_i	The mean of the squares of the vertical distances
$S_{y'}$	The standard error of the estimated values
S_y^2	The overall variance
r	Coefficient of correlation
U(A)	Utility of a prize A
BEMU	Break even mark-up
n,λ	number of competitors
e	expected frequency
o	observed frequency

$R(\beta_o)$	Variation due to mean
$R(\beta_1/\beta_o)$	Variation due to regression
$\hat{\beta}_o, \hat{\beta}_1$	Estimates of β_o and β_1
$R(\beta_o\beta_1)$	Reduction due to β_o and β_1
H_o	Null hypothesis
v	Coefficient of variation
ER	Estimation accuracy
M	Mark-up
ER(US)	Estimation accuracy of the last contractor
ER(THEM)	Estimation accuracies of the competitors
ER(ALL)	Estimation accuracies of the last contractor and his competitors
M(US)	Mark-up of the last contractor
M(THEM)	Mark-ups of the competitors
M(ALL)	Mark-ups of the last contractor and his competitors
BN	Bidder number
ANP	Average net profit
PRN	pseudo random number
NAG	Nottingham algorithm group.

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CHAPTER ONE

INTRODUCTION

There are some contractors who believe, with justification, that contracts are won or lost by sheer chance. However, a fact that cannot be denied is the existence of a relation between the bid price and the probability of winning the tender. Every bid submitted is sandwiched between the two limits of: being too high and, thus, ensuring a profit, if successful, but having a low probability of success, or, being too low and thus resulting in a loss but having a high success rate. The probability of success, associated with bid prices between these two limits, has been a subject for research carried out by several authors, which resulted in the introduction of various models capable of estimating this probability.

Most of the bidding strategy models are aimed at maximizing the expected value of the contractors profit. In some special cases the contractor's objective from tendering is not making a profit and some models which take the contractor's work load into consideration were also introduced.

In general, bidding strategy models require the analysis of the past behaviour of the contractor and his competitors in order to predict their future behaviour. Therefore a large volume of relevant bidding data is required; this is a problem in itself for civil engineering contracts, where it can be said that no two contracts are alike.

Another problem associated with bidding data is its availability, as most contractors are reluctant to give any information which they fear can be used to discover their strategies and/or bidding behaviour. However, two sets of data were obtained for this investigation and their analysis is presented in Chapter 4.

An alternative approach to bidding strategy is that of applying operational research techniques solved by numerical methods. A widely used numerical method is that of simulation which uses random sampling in the solution process. The use of random numbers is central to the application of a simulation technique, and the accuracy of the results depend on their degree of randomness. Pseudo-random numbers are the form of random numbers suitable for computer programming and a sub-routine for their generation was written and tested.

Several concepts of the theory of bidding strategy were studied and the influence of important parameters, such as the number of competitors, the estimation accuracy, and the applied mark-up were analysed using computerised simulation. The results of these investigations are presented in Chapter 5.

During the time period available for this research, it was not expected that all aspects of a theory as wide and as diverse as that of bidding strategy would be covered. Therefore, some important bidding situations were not simulated, due to the lack of time, and were left as subjects for future research. A brief summary of these situations is presented in Chapter 6.

The objective of this work was to investigate the possible application of the technique of computerised simulation to study the effects of the various bidding parameters (e.g. number of competitors, estimation accuracy and job value) on success ratio, average net profit, etc. A set of typical situations is arrived at, which can be used by a contractor to supplement, not replace, his subjective assessment of a particular bidding situation.

CHAPTER TWO

ESSENTIALS OF STATISTICAL THEORY

2.1 Introduction

The method used by a contractor to achieve his aims from entering into a bidding competition is called the bidding strategy of the contractor. The fact that, even when using the same strategy, the contractor might finish at either end of his competitors range of bids for different contracts, justifies the belief that contracts are won by the chance occurrence of some estimator's mistake. Although the winning of a contract with the required profit margin remains an uncertainty, several models have been developed to assist the contractor by predicting the success ratio associated with each mark-up he may decide to use. All these models, which will be described in the next chapter, are based on studying the bidding history of the contractor and his competitors in order to predict their future behaviour. Statistical theory, which can test if data sets are representative of a wider group and test if conclusions based on it can be applied to the whole group, is used extensively in bidding strategy.

For the convenience of reference, a summary of some of the essential results of statistical theory is presented in this chapter.

2.2 Averages

An important way of describing a group of numbers is averaging, in which a single numerical value represents the group. There are three averages: the mean, the median, and the mode, of which the most commonly used is the mean. There are three types of means,[1]:

1) The arithmetic mean: This is the average of a set of numbers and is given by:

$$AM = \bar{x} = \frac{\Sigma x}{n} \tag{2.1}$$

where x = the value of each score to be averaged

n = the number of scores averaged.

2) The harmonic mean: This mean is used when the time factor is the variable and is given by:

$$HM = \frac{n}{\Sigma\ (\frac{1}{x})} \tag{2.2}$$

3) The geometric mean: This method of averaging cannot be used when one score is zero or has a negative value and is given by:

$$GM = \sqrt[n]{(x_1)(x_2)\ldots\ldots(x_n)} \tag{2.3}$$

The mean is defined as that point about which the sum of the deviations is zero. The deviations are sometimes referred to as moments.

The median is defined as the point in a distribution with an equal number of cases on each side of it.

The third average, the mode, is defined as the datum value which occurs most frequently. It can also be defined as the midpoint of the interval containing the largest number of cases in a frequency table.

The mean deviation, M.D., of a set of variates is defined as the arithmetic mean of their absolute deviations from their arithmetic mean:

$$M.D = \frac{1}{n} \sum_{i=1}^{n} \left| x_i - \bar{x} \right| \tag{2.4}$$

It is important to distinguish between the true population parameters and those of a sample of n randomly selected observations. If the population has a mean (μ) and a standard deviation (σ), then the sample mean ($\bar{x}$) is an intuitive estimate of (μ).

The variance of the sample (S^2) is given by:

$$S^2 = \frac{1}{n-1} \sum_{i=1}^{n} (x_i - \bar{x})^2 \tag{2.5}$$

The standard deviation is the positive square root of the variance:

$$S = \left[\frac{1}{n-1} \sum_{i=1}^{n} (x_i - \bar{x})^2 \right]^{\frac{1}{2}} \tag{2.6}$$

In the rare case when the population mean (μ) is known then the variance (σ^2) is given by:

$$\sigma^2 = \frac{1}{n} \sum_{i=1}^{n} (x_i - \mu)^2 \tag{2.7}$$

and the standard deviation is:

$$\sigma = [\frac{1}{n} \sum_{i=1}^{n} (x_i - \mu)^2]^{\frac{1}{2}} \tag{2.8}$$

However it -can be shown that S^2 is an unbiased estimate of the true population variance σ^2, [2].

2.3 Probability distribution

An important concept in probability is the idea of a probability distribution. These distributions can be of a variable (X) which takes a discrete or continuous form.

In the discrete case, a variable (X) can take values $x_1, x_2, \ldots x_n$ with probabilities $p_1, p_2, \ldots p_n$, where $p_1 + p_2 + \ldots p_n = 1$ and $p_i \geqslant 0$ for all i. This defines a discrete probability distribution for X Fig. (2.1). The probability that X takes a value of (x) is denoted by $P(X = x)$, and the sum of the probabilities is defined as:

$$\sum_{i=1}^{n} p_i = 1 \tag{2.9}$$

The expected value E(X) is given by:

$$E(X) = \sum_{i=1}^{n} x_i p_i \tag{2.10}$$

The observations of a continuous variate can be plotted as a histogram. As the number of observations is increased, the histogram approaches a smooth curve called the frequency curve, Fig. (2.3).

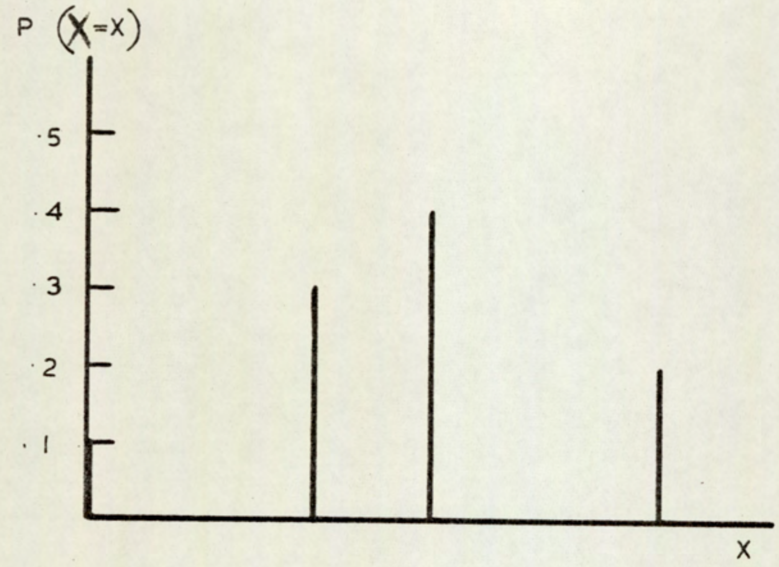


Fig. 2.1

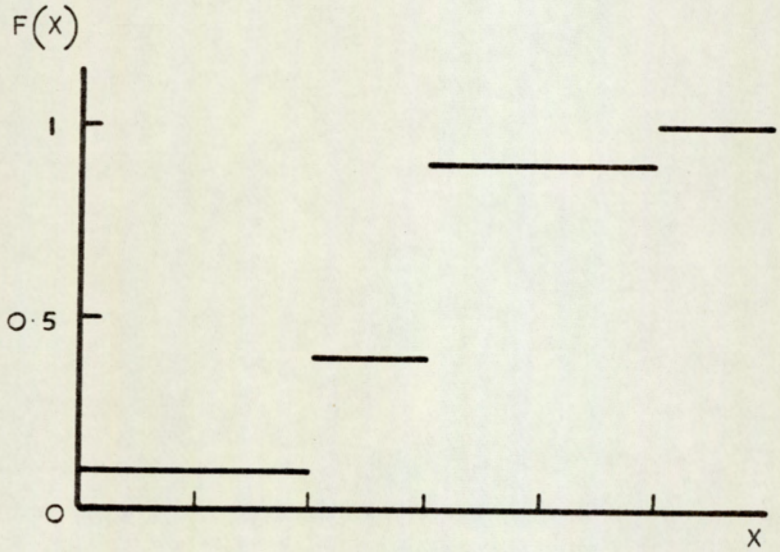


Fig 2.2

If the height of this curve is standardised, so that the area underneath it is unity, it is called the probability curve. The probability density function (p.d.f) $f(x)$,is the height of the probability curve at a point x. From definition:

$$\int_{-\infty}^{\infty} f(x)dx = 1 \tag{2.11}$$

And the expected value is given by:

$$E(X) = \int xf(x)dx \tag{2.12}$$

In the continuois case the probability of an observation falling in a given range can be found only and is given by:

$$P(x_1 < X < x_2) = \int_{x_1}^{x_2} f(x)dx \tag{2.13}$$

Another way of describing a probability distribution is by specifying the cumulative distribution function (c.d.f), which is defined as the probability of observing a value less than or equal x:

$$F(x) = P(X \leqslant x) \tag{2.14}$$

The c.d.f. can describe both discrete and continuous distribution. In the discrete case it is a step function rising from 0 to 1, Fig.(2.2).

For the continuous case

$$F(x_0) = \int_{-\infty}^{x_0} f(x)dx \tag{2.15}$$

and

$$P(x_1 < X < x_2) = F(x_2) - F(x_1) \tag{2.16}$$

It also rises from 0 to 1 as Fig. (2.4):

$$F(-\infty) = 0 \tag{2.17}$$

and

$$F(\infty) = 1 \tag{2.18}$$

2.3.1 Discrete random variable distributions

A) The binomial distribution: The distribution is expressed as,

$$P(X=x) = \binom{n}{x} p^x q^{n-x} \tag{2.19}$$

where:

$$\binom{n}{x} = \frac{n!}{x!(n-x)!} \tag{2.20}$$

and

p: the probability of success of any given trial

q: the probability of failure of any given trial

n: number of independent trials

x: number of successes

P(X=x): probability of x successes in n trials.

The theoretical mean of binomial distribution is:

$$\mu = np \tag{2.21}$$

It can be shown that the expected value of a binomial distribution is:

$$E(X) = np \tag{2.22}$$

The variance of X for this distribution is given by

$$V(X) = np(1-p) \tag{2.23}$$

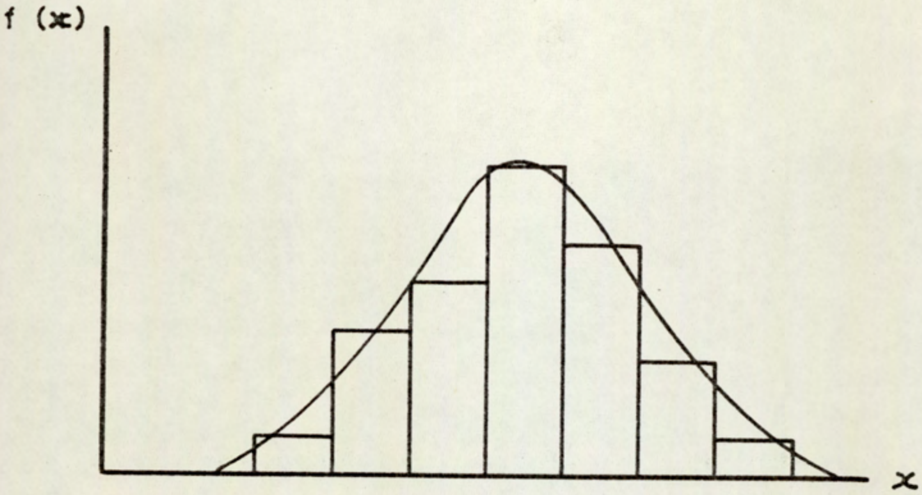


Fig. 2.3

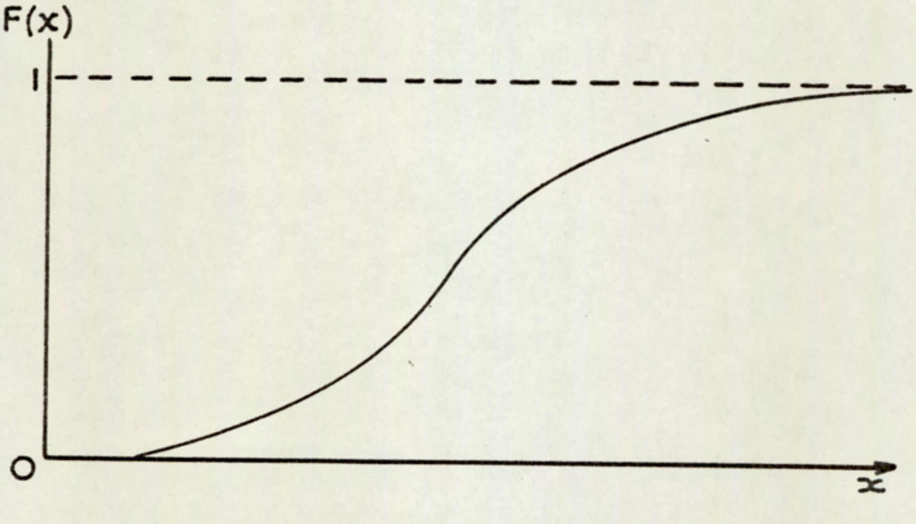


Fig .2.4

and hence the standard deviation σ is given by $\sqrt{np(1-p)}$. The shape of this distribution is shown in Fig. (2.5).

B) The Poisson distribution: The form of this distribution is given by:

$$P(X=r) = \frac{e^{-\mu}\,\mu^{r}}{r!} \tag{2.24}$$

where $r = 1, 2, \ldots$

μ = mean

and its shape is shown in Fig. (2.6).

This distribution describes, satisfactorily, the occurrence of an isolated event x in terms of the mean number of occurrences of these events μ.

The expected value is:

$$E(X) = \mu \tag{2.25}$$

and the variance,

$$V(X) = \mu \tag{2.26}$$

C) The negative binomial distribution: considering the binomial distribution given by equation (2.19). If it is required to find the probability of the x^{th} success on the n^{th} trial, which can occur only if in the first (n-1) trials, there are exactly (x-1) success, i.e.

$$P(X = x-1) = \binom{n-1}{x-1} p^{x-1} q^{n-x} \tag{2.27}$$

and the next trial results in a success, therefore

$$P(X = x) = \binom{n-1}{x-1} p^x q^{n-x} \tag{2.28}$$

This equation defines a negative binomial probability distribution:

D) The geometric distribution: This is a special case of the negative binomial distribution and is given by:

$$P(X = x) = pq^{x-1} \tag{2.29}$$

where $x = 1, 2, \ldots$

Which gives the probability that the first success occurrs after x failures.

The expected value is given by,

$$E(X) = \frac{1}{p} \tag{2.30}$$

and the variance by,

$$V(X) = \frac{q}{p^2} \tag{2.31}$$

2.3.2 <u>Continuous frequency distribution:</u>

A) The uniform (rectangular) distribution: It is a constant over an interval (a,b) and is 0 elsewhere, i.e.

$$\begin{aligned} f(x) &= (b - a)^{-1} \qquad a < x < b \\ &= 0 \qquad\qquad\qquad \text{elsewhere} \end{aligned} \tag{2.32}$$

Its p.d.f. and c.d.f. are shown in Figs.(2.7) and (2.8).

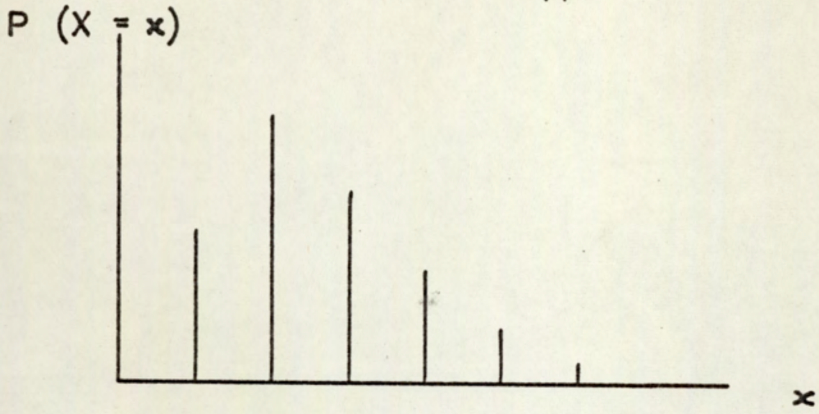


Fig . 2.5

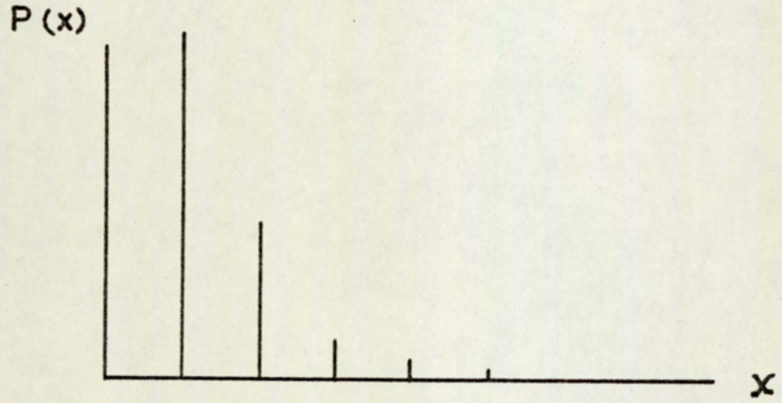


Fig . 2.6

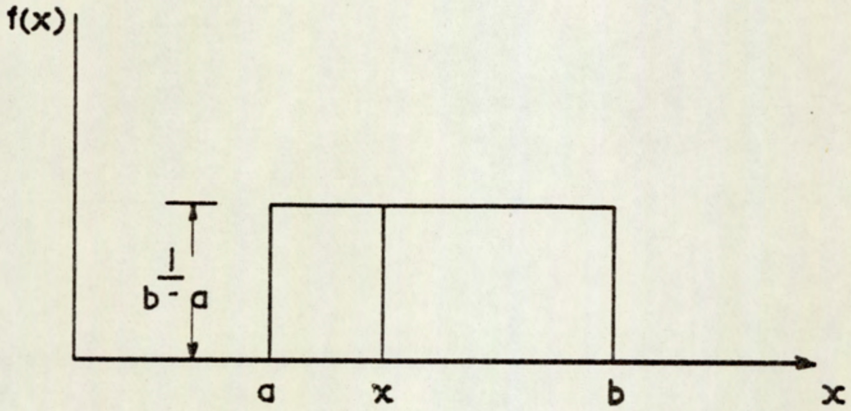


Fig 2.7

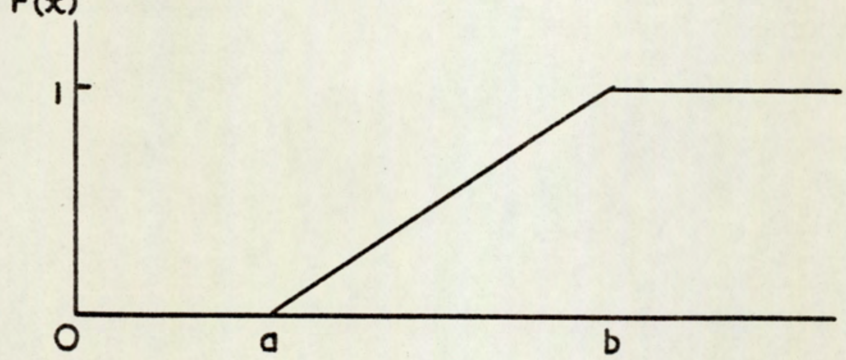


Fig 2.8

The probability of an observation falling in any interval $c < x < d$ within (a, b) is equal to $(b-a)^{-1}$ times the length of interval, i.e.

$$P(c<x<d) = (b-a)^{-1} \int_c^d dx = \frac{d - c}{b - a} \qquad (2.33)$$

B) The normal distribution: The probability density function for this distribution is given by:

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-(x-\mu)^2/2\sigma^2} \qquad (2.34)$$

where μ = mean

σ = standard deviation

The shape of this distribution is shown in Fig. (2.9), where it can be seen that there are two parameters which determine the position and relative proportions of the normal curve.

It is sometimes required to employ the density function that is independent of the units used. The standard deviate, Z, is used

$$Z = \frac{x - \mu}{\sigma} \qquad (2.35)$$

whose effect is to place the origin of Z at the mean μ and to use σ as a horizontal measure. The curve is now known as the standard form of the normal density function and is expressed as $\phi(x)$.

The standardised normal distribution has a mean of zero and a variance of unity.

C) The Gamma distribution: The Gamma function (Γ) is defines as:

$$\Gamma(p) = \int_{0}^{\infty} x^{p-1}e^{-x}dx \tag{2.36}$$

where, $p > 0$

X has a Gamma probability distribution if its p.d.f. is given by:

$$f(x) = \frac{\alpha}{\Gamma(r)}(\alpha x)^{r-1}e^{-\alpha x} \qquad \text{if } x > 0 \tag{2.37}$$

$$\text{and} = 0 \qquad \text{elsewhere}$$

This distribution depends on two parameters r and α, both of which are required to be greater than zero and its shapes for various values of r are shown in Fig. (2.10).

The expected value is:

$$E(X) = r/\alpha \tag{2.38}$$

and the variance

$$V(X) = r/\alpha^2 \tag{2.39}$$

A special case of this distribution, where $\alpha = \frac{1}{2}$ and $r = n/2$ (n = positive integer), is the chi-square distribution whose p.d.f. is:

$$f(Z) = \frac{1}{2^{n/2}\Gamma(n/2)} Z^{(n/2)-1}e^{-Z/2} \quad , Z > 0 \tag{2.40}$$

and

$$E(Z) = n \tag{2.41}$$

$$V(Z) = 2n \tag{2.42}$$

The family of curves given by the gamma distribution for different values of r = 1, 2, 3 etc. all have the same expected value.

Another special case of the gamma distribution is where r = 1, is covered in the following section.

D) The exponential distribution: The probability density function of this distribution is given by,

$$f(x) = \lambda e^{-\lambda x} \quad \text{if } x > 0 (\lambda > 0), \tag{2.43}$$
$$= 0 \quad \text{if } x < 0$$

and the cumulative distribution function by,

$$F(x) = 1 - e^{-\lambda x} \quad \text{if } x \geqslant 0, \tag{2.44}$$
$$= 0 \quad \text{if } x < 0.$$

It can be shown that the expected value is,[32]:

$$E(X) = \frac{1}{\lambda} \tag{2.45}$$

and the variance is:

$$V(X) = \frac{1}{\lambda^2} \tag{2.46}$$

The shape of this distribution is shown in Fig. (2.11).

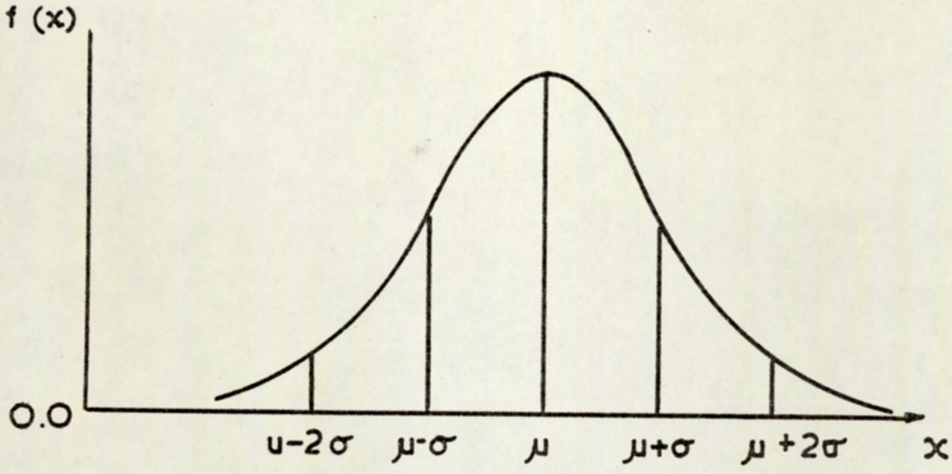


Fig . 2.9

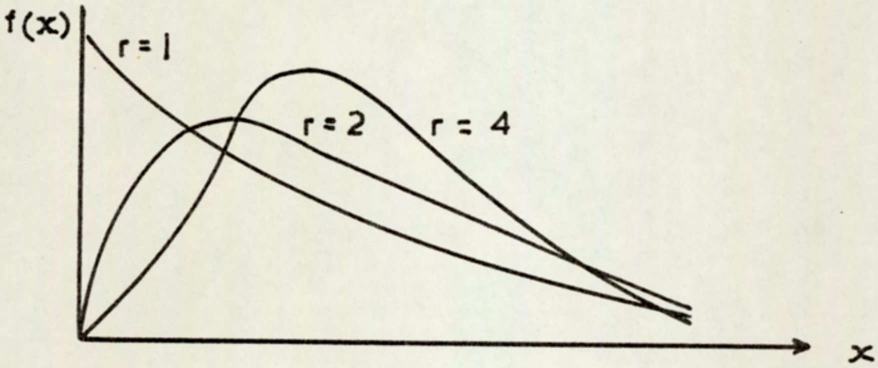


Fig. 2.10

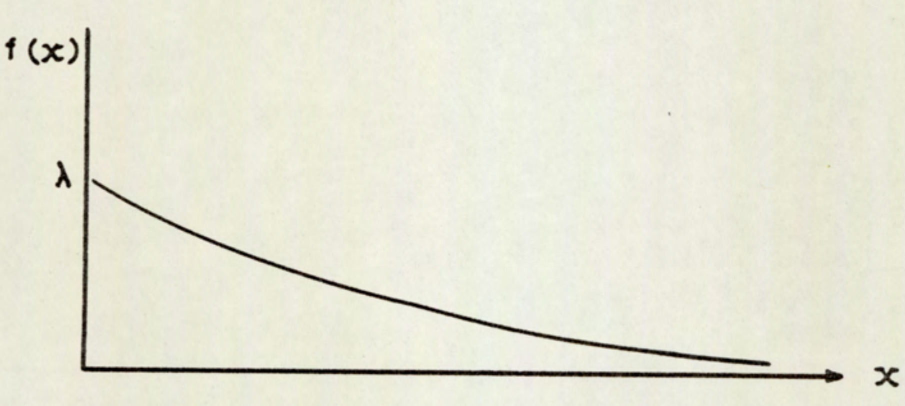


Fig .2.11

2.4 Simulation and Sampling

It is not always possible to find a mathematical solution when applying an operational research technique to a real problem. This can be attributed to the simplifying assumptions that have to be made to apply a particular technique. Hence, it becomes necessary to resort to alternative solution procedures such as numerical methods. A numerical method widely applicable is the method of simulation. This method makes use of random sampling as an essential part of the solution of problems with an explicit stochastic element.

The use of statistics is to make an inference about a larger group on the basis of information obtained from a smaller group. In other words it is required to make a statement about a population by studying one or more samples drawn from it. Samples are of two types: the non-probability type in which there is no way of estimating the probability that each element will be included, and the probability type in which each element has an equal chance of becoming a part of the sample. The work in this thesis is concerned with the second type of sample which will be discussed later in this section.

2.4.1 Simulation

The use of random numbers is central to the application of a simulation technique, and the results obtained will depend on the accuracy of the method used to generate them. A random sequence is defined as a sequence of digits formed in such a way that each one has an equal probability of appearing at each point in the sequence.

There are several tables for random numbers and various types of machines which can produce them, but to be able to use them in a simulation study, they will have to be stored (e.g. on a magnetic tape). As the study may require thousands of these numbers, this method is ruled out. An alternative will be the generation of a sequence by using predetermined conditions. This alternative implies the predictability of the sequence and hence contradicts the concept of randomness. However, the characteristics of the sequence can be compared with what is expected of a genuine random sequence; and if the difference is statistically insignificant, the sequence can be accepted as pseudo random.

For the work presented in this thesis, a computer subroutine was written to generate pseudo random numbers, and the results were subjected to several statistical tests. A detailed description of this subroutine, together with a survey of the various methods used to generate pseduo random numbers, statistical tests of randomness, and examples, will be presented in Appendix (7.1).

2.4.2 Generation of specifically distributed random variables

A pseudo random numbers generator produces values,

$$r_i = \frac{x_i}{m} \tag{2.47}$$

which are uniformly distributed over the interval (0,1).

Random variables conforming to a specific distribution may be generated by direct operations on pseudo random numbers. The two types of distributionsused in the present work are the normal and uniform distributions.

The PRN's generated are uniformly distributed by definition hence they can be used directly when sampling from a uniform distribution.

Following is a description of the generation of these variables for a normal distribution, [3]:

Generating standardised normal variates:

There are several methods which give standardised normal variates, but the one used in this work which results in independent ones is due to Box and Muller,[4]. The method is based on selecting two random numbers (r_1) and (r_2) and evaluating,

$$Z_1 = (-2 \ln r_1)^{\frac{1}{2}} \cos 2\pi r_2 \tag{2.48}$$

and

$$Z_2 = (-2 \ln r_1)^{\frac{1}{2}} \sin 2\pi r_2 \tag{2.49}$$

where Z_1 and Z_2 = two independent standardised normal variates.

2.5 Regression and Correlation

2.5.1 Introduction

It is often required to fit a curve to a set of plotted points to discover or measure a trend or a relationship, if it exists. The curve fitting operation can be carried out in three stages: the decision on the type of curve, the calculation of the constant of the curve to fit the data, and the interpretation of the results. The only type of curve fitted to data throughout the present work is the straight line and hence it is the only one discussed in this section. In studying the relation between two variables x and y, a dot diagram and least square line may be used. Such a line is called a regression line.

In a regression problem it is known or suspected that one variable x is the cause of the variation in the other variable y.

Correlation can be defined as the amount of similarity in direction and degree of variations in corresponding pairs of observations of two variables. A problem of simple correlation is that of determining the degree of association between these pairs of observations.

In a pure regression problem, there is an independent variable x and a dependent one y. While in a pure correlation problem, a sample of pairs of observations are chosen from a bivariate population in which the functional relationship, if it exists, is reversible.

2.5.2 The method of least squares

A linear equation is that of a straight line and is given by:

$$y = mx + b \tag{2.50}$$

where b = the point of intersection with the Y-axis

m = the slope of the line.

It is sometimes required to find the equation of a straight line which fits best a set of points, i.e. to evaluate the parameters b and m of equation (2.50).

The least square method assumes that the best fitting line is the one for which the sum of the squares of the vertical distances of the points (x_i, y_i) from the line is a minimum. Considering a point -

$P_i(x_i, y_i)$, the ordinate of a point Q_i on the straight line vertically above or below P_i can be found. The coordinates of Q_i will be $(x_i, mx_i + b)$. The vertical distance e_i between P_i and Q_i is given by:

$$e_i = y_i - (mx_i + b) \tag{2.51}$$

The quantity e_i can be positive or negative and is referred to as the residual or error.

According to the least square method, the best-fitting line is that for which the sum of squares of the errors is a minimum, i.e.

$$\Sigma\, e_i^{\,2} = \text{minimum} \tag{2.52}$$

The problem is reduced to find the parameters m and b which satisfy the condition stipulated in equation (2.31). It can be shown that these values are, [5]:

$$b = \frac{\Sigma x_i^{\,2}\ \Sigma y_i - \Sigma x_i\ \Sigma x_i y_i}{N\Sigma x_i^{\,2} - (\Sigma\, x_i)^2} \tag{2.53}$$

$$= \bar{y} - m\bar{x} \tag{2.54}$$

and

$$m = \frac{N\Sigma x_i y_i - \Sigma x_i\ \Sigma y_i}{N\Sigma x_i^{\,2} - (\Sigma x_i)^2} \tag{2.55}$$

2.5.3 A study of the regression trend and the variance of the errors

The regression trend can be studied by observing the slope of the regression line, and if the line has no upward or downward trend (positive or negative slope), i.e. it is parallel to the x-axis, it can be concluded that the value of y is not influenced by that of x.

If all the points lie on the regression line it can be concluded that the relation is expressed in terms of the equation,

$$y = mx + b \tag{2.56}$$

and the variance S_y^2 is the mean of the squares of the lengths of the vertical line segments between each point and the one above or below it on a horizontal line $\bar{y}$, Fig. (2.12).

However, in the general case the points do not lie on the regression line, which implies that some, but not all, the variability in y can be explained by regression. The values e_i are used to measure the variability that regression cannot explain.

For every point (x_i) there are two values: y_i given by the data, and y_i' from the equation of the regression line.

$$y_i' = mx_i + b \tag{2.57}$$

The value e_i for these points is given by:

$$e_i = y_i - (mx_i + b) \tag{2.58}$$

$$= y_i - y_i' \tag{2.59}$$

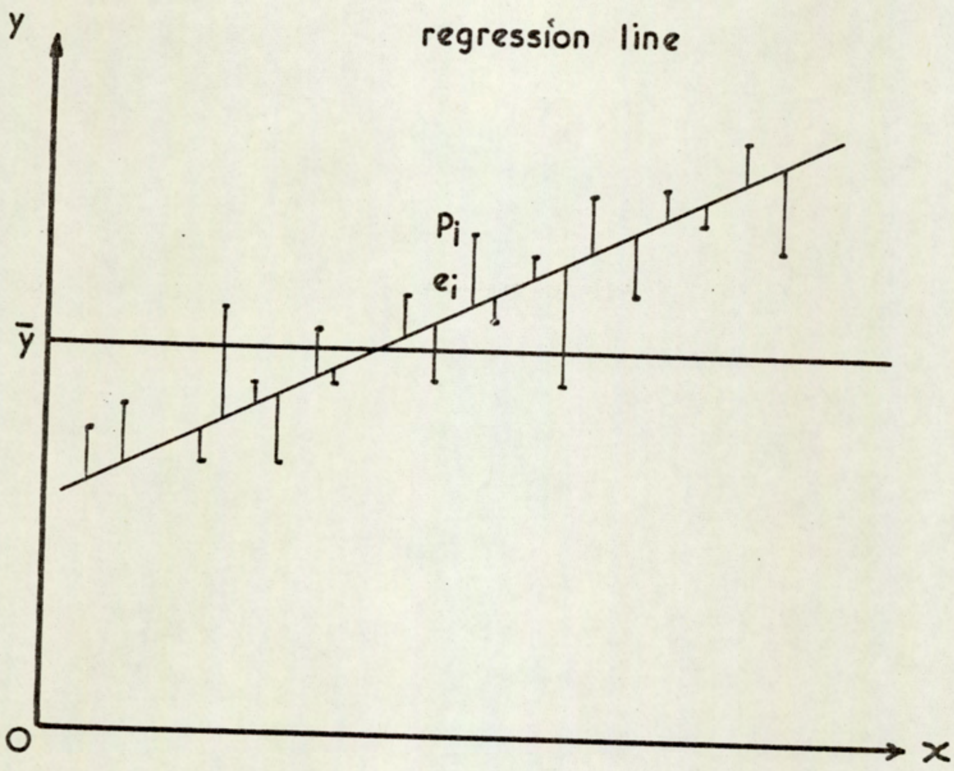


Fig . 2.12

It can be shown that the mean of the estimated y''s is equal to the mean of the observed y's,[5]:

$$\bar{y}' = \bar{y} \qquad (2.60)$$

The mean of the squares of the vertical distances e_i, is called the variance of the errors of the estimate and S_e, which is the standard error of the estimate, is given in terms of it by:

$$S_e^{\,2} = \frac{1}{N} \Sigma \, e_i^{\,2} \qquad (2.61)$$

Sy', is the standard error of the estimated values and is given by:

$$S_{y'}^{\,2} = \frac{1}{N} \Sigma \, (y_i' - \bar{y}')^2 \qquad (2.62)$$

It can be shown that, [5]:

$$S_y^{\,2} = S_e^{\,2} + S_{y'}^{\,2} \qquad (2.63)$$

This relation shows that the overall variance, $S_y^{\,2}$, can be divided into two parts, the explained variance, $S_{y'}^{\,2}$ and the unexplained variance, $S_e^{\,2}$.

2.5.4 <u>The two lines of regression</u>

In a correlation it is useful to consider two lines of regression: the y on x described previously, and the x on y. In the new line x on y, the sum of squares of the horizontal distances is minimized. The equations are obtained by interchanging the x and y, hence:

$$x = m'y + b' \tag{2.64}$$

$$m' = \frac{N\Sigma xy - \Sigma x\Sigma y}{N\Sigma y^2 - (\Sigma y)^2} \tag{2.65}$$

$$b' = \bar{x} - m'\bar{y} \tag{2.66}$$

2.5.5 <u>The coefficient of correlation</u>

The ratio of the explained variances to the unexplained ones is given by:

$$r^2 = \frac{Sy'^2}{Sy^2} \tag{2.67}$$

It can be seen that if all the points lie on the regression line, i.e. $S_{y'}^2 = S_y^2$ the coefficient is (r=1), and if no regression exists then $S_{y'}^2 = 0$ and hence ($r^2 = 0$), the ratio

$$r = \pm \frac{S_{y'}}{S_y} \tag{2.68}$$

is called the coefficient of correlation.

It can be shown that, [5],

$$r = \frac{mSx}{S_y} \tag{2.69}$$

where m = regression coefficient

and that

$$r = \frac{1}{N}\Sigma \left(\frac{x-\bar{x}}{Sx}\right)\left(\frac{y-\bar{y}}{Sy}\right) \tag{2.70}$$

It must be noted that a high correlation coefficient between two variables does not necessarily indicate the existence of a relationship.

A third variable can cause simultaneous changes of the two variables resulting in a spuriously high correlation coefficient, [2]. Therefore a controlled experiment needs to be run in order that a relationship is established as will be seen later in Chapter 4.

CHAPTER THREE

LITERATURE SURVEY

3.1 Introduction

The method of competitive tendering, in which a number of contracting companies are invited to submit closed bids, is the one which is mostly used in awarding contracts; and the lowest bidder is usually the successful one. Therefore a contractor can apply a very low mark-up, risking ending up with a loss but ensures obtaining the contract, or bid with a very high mark-up and hence ensuring making a profit but decreasing his chances of being the successful bidder. It is clear that, knowledge of the probability of winning a tender, associated with each particular mark-up would be very valuable to the contractor. A lot of research had been carried out to produce a probabalistic model capable of supplying this information and some research workers have attempted to predict from their models an optimum mark-up which will achieve the best balance between the profit realized from a contract and the chance of securing it. Although most of the published work in the field of bidding strategy is dedicated to the determination of such a model, it must be pointed out that the short-run objectives of some of the bidders is not to maximize profit. Alternatively, the objective can be minimize competitor's profits, maintain a work force during a slack period, or increase his share of the market. In cases like these the basic probabalistic model is weak because it does not take the contractors work load into consideration.

It must be noted that the mark-up is not the only variable controlling the probability of winning. As it is applied to an estimated cost of the contract, any errors in this estimation will effect the final tender value. This is the basis of the belief that contracts are won by the bidder who makes the biggest mistake.

Other factors which have some bearing on the probability of winning are the number of competitors and the tender value.

A survey of the published literature in these areas will be presented and discussed in the following sections of this chapter.

3.2 The basic concepts of bidding

In all probabalistic bidding strategy models, a relationship between the tender price and the probability of winning is assumed to exist. However, the mathematical expression defining this relationship differs from one model to another. There are two extreme cases for which the results are almost certain:

1) To bid very low and thus secure the job but make no profit or even lose money.
2) To bid very high to ensure a high profit but the chances of winning are virtually nil.

Between these two extremes there are corresponding probabilities of success for each tender.

3.2.1 The concept of expected profit

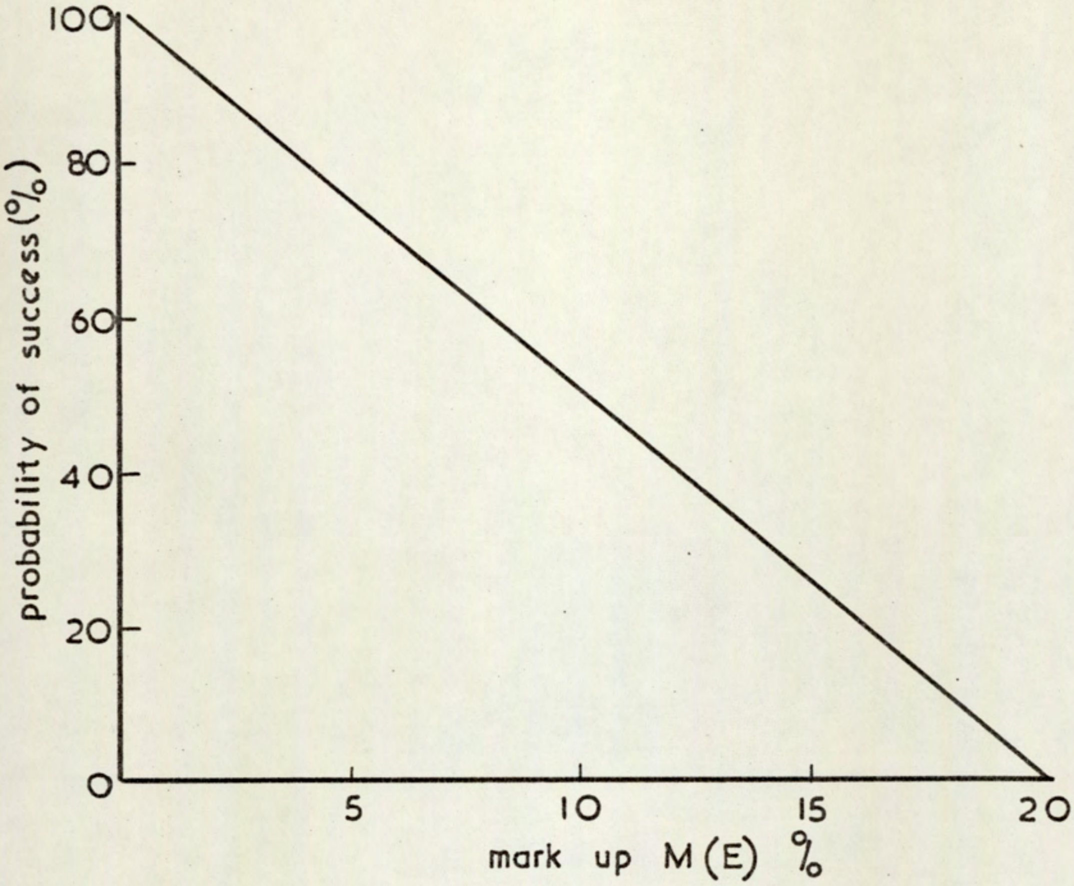
It is seen that a relationship exists between the probability of winning and the tender price submitted. Assuming that all competitors maintain the same estimation accuracy in all their bids this relation can be transformed to one between the applied mark-up and the probability of success.

This concept was introduced by Friedman, [6], and later used in the models of Gates, [7], Whittaker, [8], Morin and Clough, [9], and several others.

Each one of these authors had his own probabilistic model, therefore, to introduce this concept, a hypothetical linear model is assumed, Fig. (3.1). For every mark-up there is a corresponding success ratio and hence an average net profit. The average net profit is the total profit made from the winning bids divided by their number. The product of the success ratio and the average net profit for various mark-ups has the form shown in Fig. (3.2), where it is seen that there is an optimum mark-up which maximizes the expected profit.

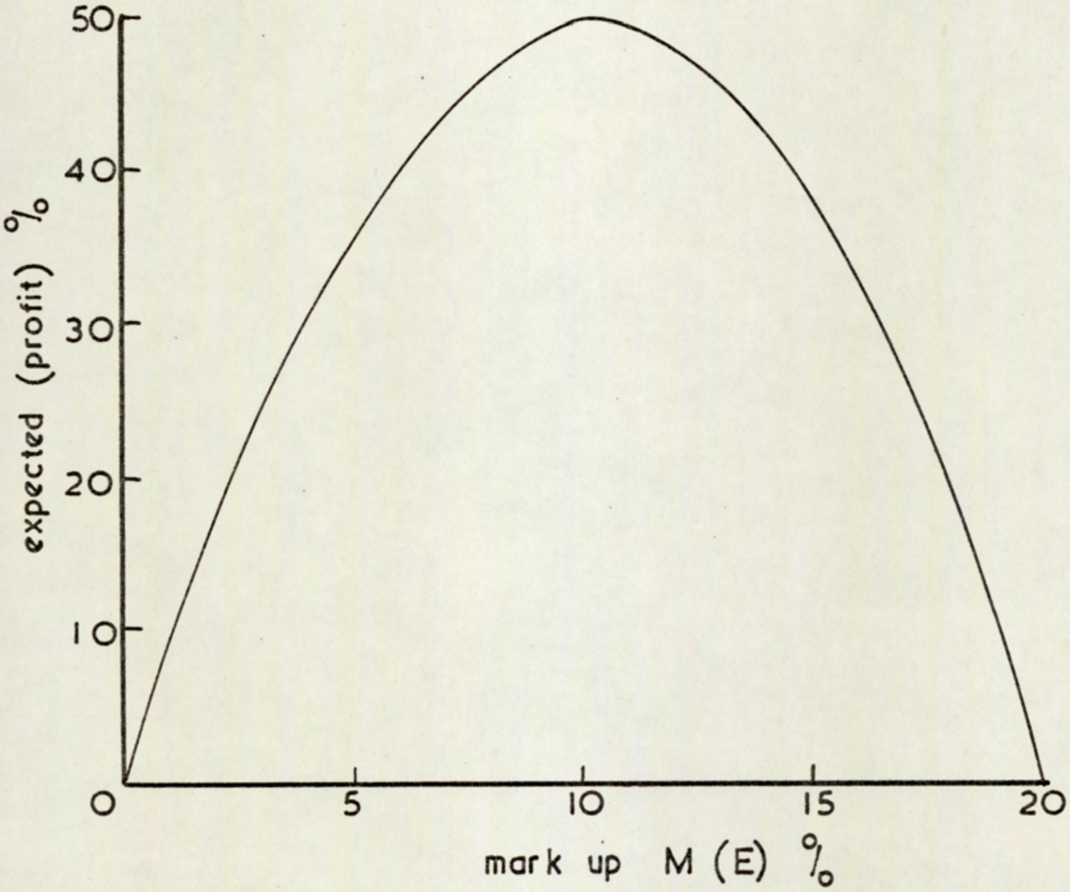
3.2.2 The concept of the expected utility value

The bidding process can be viewed as a process of decision making, one of which is the determination of the mark-up. As each level of mark-up is associated with a success ratio, it appears to be logical that a decision maker will try to find an optimum level of mark-ups, for each bidding situation, which maximizes the expected value. This value can be viewed as either, the amount of money which



100
80
60
40
20
0
probability of success (%)
5
10
15
20
mark up M (E) %

Fig. 3.1



50
40
30
20
10
0
expected (profit) %
5
10
15
20
mark up M (E) %

Fig 3.2

may be obtained or, the utility value equivalent which he assigns to this amount of money, with the utility being defined as a number between 0 and 1 measuring the attractiveness of a consequence. There are several available models,as will be seen in the following sections, for maximizing the expected monetary value. However, there are some models in the published literature which suggest maximizing the expected utility value, [11]. Following is a brief description of this concept.

A) Utility functions:

The modern utility theory is due to Neumann and Morgenstern, [12], who based it on a set of axioms which an individual must satisfy in order that the utility function has a meaning. An intuitive definition of these assumptions is listed as six axioms,[13]. One of these axioms implies that there is a probability value between 0 and 1 $(0 < P < 1)$ for which the decision maker is indifferent between a certain prospect M_1 and an uncertain one composed of M_2 with a probability of P and M_3 with a probability (1-P), Fig. (3.3), where it can be seen that the indifference point can result from a probability (P) for which the individual is indifferent between a sure prize of B or a chance of either prize A or C. If it is assumed that $A \succ B \succ C$, then a probability P near to 1 will make the choice of risk more attractive as it may result in prize A, while a P value near to 0 will make the choice of certainty more attractive as the lottery may result in C. The equation which represents this situation in, [14]:

$$U(B) = PU(A) + (1-P)U(C)$$

where:U(A), U(B) and U(C) are the utility equivalents or prizes A, B and C.

B) Basic shapes of utility functions:

It has been seen that utility varies from 0 to 1 with the value of 1 awarded to an infinitely attractive consequence. However, in practice, it is assigned to what is known as the upper financial horizon. There are three basic shapes of utility functions shown in Fig. (3.4). All three types increase monotonically ($\frac{dU}{dM} > 0$), i.e. prefering more money to less, but their attitude to extra gain differs. Type I has a constant marginal utility ($d^2U/dM^2 = 0$), i.e. the last lot of money is as attractive as the first. Type II has a decreasing marginal utility ($d^2U/dM^2 < 0$), i.e. the last lot is less valuable than the first. Finally, type III values the money gained more, the more of it is gained ($d^2U/dM^2 > o$). A contractor with a type III utility curve is willing to take an unfair risk, while one with a type II curve prefers certainty.

A type II utility curve will be applied to a contractor's data, in view of finding an optimum mark-up at a later stage, as an example for the application of the theory presented in this section.

3.2.3 The concept of target probability

In the concept of expected profit, the work load of the contractor is ignored. Trimble, [10] introduced the concept of a target success ratio for the contractor to aim at when deciding on his mark-up policy. The contractor is assumed to plan a required turnover over a period of time. This time period is limited by his ability to plan his work requirements and his profitability will depend on the correct assessment of the required turnover.

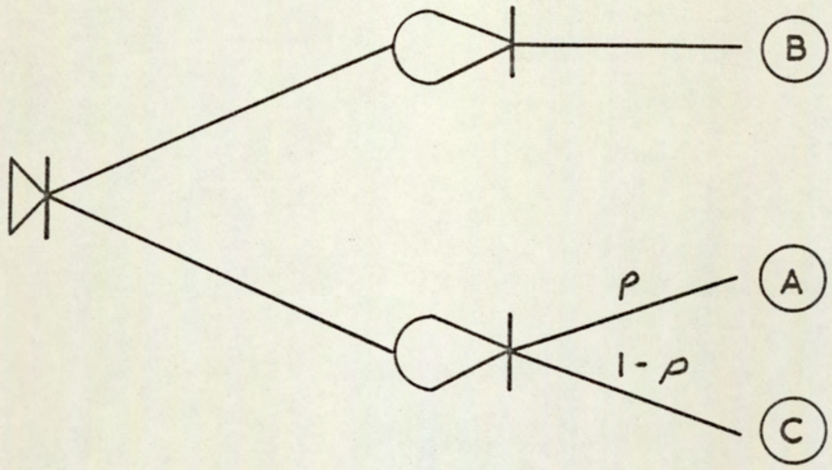


Fig .3.3

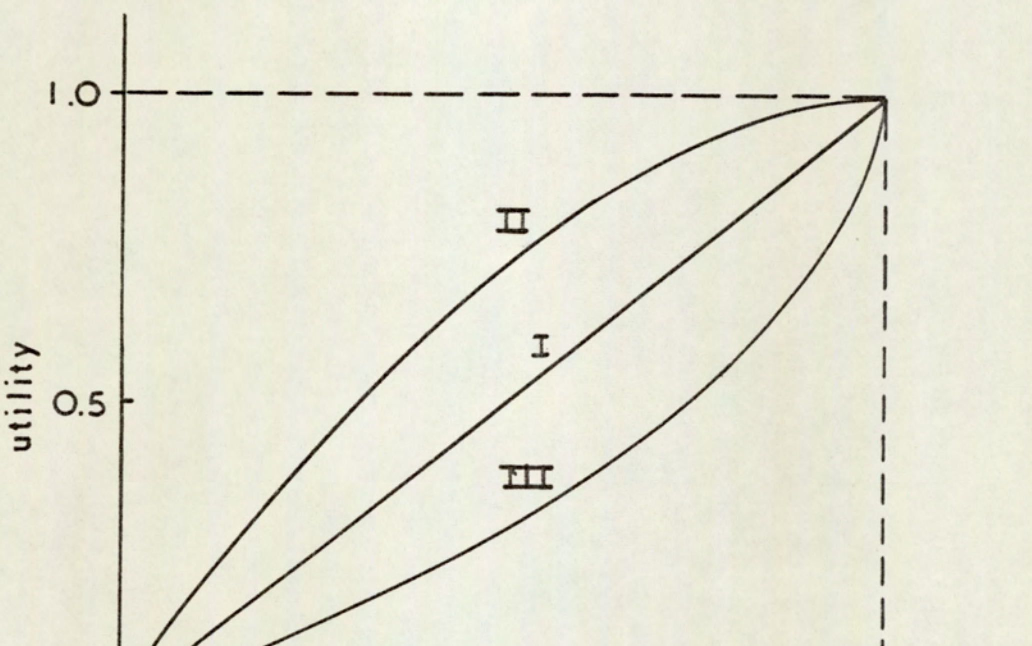


Fig.3.4

By breaking up the time period into sub-sections, the contractor can compare his actual work load with the required turnover and determine a success ratio which enables him to meet it. The mark-up corresponding to this success ratio is applied over the next time sub-section after which a similar assessment is made.

3.3 The probability of winning

3.3.1 Introduction

Several investigators have proposed a number of competitive bidding strategy models. To be able to use these models, it is necessary to define the objective aimed at, and to develop a probability distribution to assess the probability of winning with a given mark-up. With few exceptions, bidding models have adopted the concept of maximizing expected profit discussed in section (3.2.1). However, there is a lot of disagreement in assessing the probability of winning with a given mark-up.

Following is a critical review of the important models available.

3.3.2 Friedman's model

Friedman, [6], was the first to develop a relationship between the probability of winning and the mark-up and most of the models that followed were based on his model as will be seen later. This model will be examined at this stage for the simple case of a single competitor.

The method requires the collection of data on bid prices of this competitor in several previous tenders in which we have competed with him. A histogram is built from the ratio r (competititor bid/our cost estimate) and the particular class of the bid value. This histogram can be converted to a probability density function. A statistical distribution can be fitted and the goodness of fit tested. The suitable statistical distribution, which is usually a normal or a gamma one, is used to evaluate the probability of success associated with each mark-up when competing against this particular competitor.

In practice the number of competitors is normally more than one and they can be known or unknown to us. Following is a description of this model for the two situations.

A) Known competitors:

The model again assumes that it is possible to construct a distribution similar to that of the case of a single competitor for each one of the competitors. According to Friedman:

The probability of winning a contract at a given mark up = (Prob. of beating A) x (Prob. of beating B) x (probability of beating C)... etc.

B) Unknown competitors:

In this situation all the competitors bids are aggregated into a single distribution, which will be similar to that of the single competitor. The distribution may be considered as that of a "typical competitor". For this case Friedman suggests that:

The probability of winning against 'n' unknown competitors for a given mark-up = (Probility of beating the typical competitor)^{n}.

Friedman suggests a relationship between the job value and the number of competitors. He argues that higher cost jobs attract more competitors. This suggestion was a subject for discussion by other authors as will be seen later.

This model assumes implicitly that the probabilities of beating a competitor are statistically independent. From the definition of independence:

Probability (contractor beating A & B) =

Prob.(contractor beats A) x Prob.(contractor beats B).

Therefore for 10 evenly matched contractors competing for the same job, the probability of one of them being the winner is:

Prob(A_1 beat A_2) x Prob.(A_1 beat A_3)...Prob.(A_1 beat A_{10})

= $(0.5)^9$ = 1/512 which is very small.

Also the sum of the probabilities of all ten contractors does not add to unity which is hard to justify as one of them must win the contract. It can be shown in fact that Friedman's model attaches a probability to the outcome "all lose", which is untrue. It assumes that each competitor is paired successively with each of the other competitors and the successful competitor must win all of these competitions.

Another criticism of this model is that it includes, indiscriminately, all competitors past bids in its distribution. As the winner is the lowest competitor, the inclusion of very high losing bids will affect the distribution.

The profit according to this model is the difference between estimated cost corrected for estimation inaccuracies and the bid amount. No allowance for overheads is made.

3.3.3 <u>Park's model</u>

This model, [15], is basically Friedman's model. Park reinforced Friedman's suggestion of the existence of a relation between the job value and number of competitors and express it as:

$$\left(\frac{N_1}{N_2}\right)^x = \frac{M_2}{M_1}$$

where N_1 and N_2 = Number of competitors on jobs 1 and 2

M_1 and M_2 = mark-ups of jobs 1 and 2

x = appropriate exponent

and that

$$\left(\frac{C_1}{C_2}\right)^x = \frac{M_2}{M_1}$$

where C_1 and C_2 = cost estimates of jobs 1 and 2.

It is not clear, however, how bidding data is required to develop the value of x. It is not known also whether the second relation assumes the same number of competitors for both jobs and what influence has this number on the relationship.

3.3.4 Broemser Model

This model, [16], like Friedman's, maximizes the expected value of a bid, but is much more complex than Friedman's. His linear model is adopted from a statistical decision theory approach suggested by Christenson, [17]. Here, low bidder j's bid/cost ratio = $\Sigma\beta_k X_{jk}$

where β_k = regression coefficient

X_{jk} = independent descriptive variable.

This model takes into account the criticism of Friedman's model that it includes all bids and is based on the lowest bid. It also does not assume independence between the probabilities of beating typical competitors.

Although this method is statically sound and superior to Friedman's, its application is difficult as it requires breaking the estimates into percentages of subcontractor work.

There is no provision in this model for estimation inaccuracies nor for over-heads.

3.3.5 Casey and Shaffer Models

Casey and Shaffer, [18] proposed two models which are an adaptation of Friedman's model. In arriving at their models, they assumed that there are no estimation inaccuracies and that the profit is given by:

$$p = b - c$$

where b = bid price

c = true cost of contract.

This reduced the problem to finding an optimum bid which maximized the expected profit.

In the multi-distribution model, normal probability distributions of the ratios of 'competitor's bids'/'our cost estimate' are constructed from data obtained from previous tenders similar to Friedman's model. It is assumed that, in a given situation, the contractor expects n known competitors, and other unknown ones, to bid against him.
In this model, the geometric mean of the probabilities of beating each of the known competitors, is taken as the probability of beating an average competitor.

$$P = \sqrt[n]{\prod_{i=1}^{n} \left[1 - F_i\left(\frac{b}{c}\right)\right]}$$

where: P = prob. of beating an average competitor

$F_i(\frac{b}{c})$ = cumulative distribution function evaluated at (b/c).

The one distribution model corresponds to Friedman's unknown competitors one with a bias correction of 1, i.e. no provision for estimation inaccuracies is made. The cost estimate was taken as 85% of the bid price, hence, it can be assumed that the cost estimate contains provisions for general overhead.

3.3.6 Gate's Model

Marvin Gates, [7], proposed a model of the Friedman type in the sense that it aims at maximizing the expected profit. However, his model differs from Friedman's by assuming that the probabilities of beating competitors is not statistically independent in the construction industry. He proposed, without a proof, the following model for beating n known competitors:

prob. of beating n known comp. =

$$\frac{1}{1 + \frac{\text{1-prob.of beating A}}{\text{prob. of beating A}} + \frac{\text{1-prob. of beating B}}{\text{prob. of beating B}} \cdot\cdot + \frac{\text{1-prob. of beating n}}{\text{prob. of beating n}}}$$

Benjamin, [11], tried to justify this model and showed the reasoning required to derive it. He wrote this model in terms of the cumulative distribution functions of the competitors bid/cost ratio as:

prob. of beating n known comp =

$$\frac{1}{1 + \frac{F_A(b/c)}{1-F_A(b/c)} + \frac{F_B(b/c)}{1-F_B(b/c)} \cdots\cdots + \frac{F_n(b/c)}{1-F_n(b/c)}}$$

where: F(b/c) has the same meaning as in section (3.3.5).

For the situation of unknown competitors, Gates in a similar way to Friedman, proposed a probability distribution function of a typical competitors bid/cost ratio. The probability of beating n typical competitors is:

$$\text{Prob.of beating n unknown comp} = \frac{1}{1 + \frac{n(1-\text{prob.of beating the typical comp.})}{\text{prob. of beating the typical comp.}}}$$

No provision for estimation inaccuracies is made in this model and the profit is taken as the difference between the bid price and the estimated cost.

The sum of the probabilities of winning for all the competitors in any bidding situation, adds up to unity according to this model. Hence, it can be argued that Gates arrives intuitively at a correct model. Gates, [7], states that there is no evidence that the number of bidders, for a construction project, is in any way related to the magnitude of the cost of the job. Hence he disagrees with Friedman and Park.

3.3.7 Optimum bid (OPBID) Model

Morin and Clough, [9], developed a computer program OPBID (Optimum bid) to evaluate the probability of success of a contractor in a particular bidding situation.

In this model, the mark-up is assumed to consist of a fixed percentage for over-heads and a variable percentage for profit.

The expected profit is maximized after subtracting the percentage of the over-heads.

The identity of the competitors was not divided into known and unknown, as in other models, but as being either key or average.

Key competitors are identified on the basis of the ratio of their past biddings to the total number of biddings which were available to them. If this ratio is greater than an arbitrary key factor between 0 and 1 they are considered to be key competitors. According to this method the values 0.4 and 0.5 yielded the best results. All other competitors are grouped into an average competitor.

Unlike other models, no attempt was made to fit a known continuous distribution function to the available data. Instead, a discrete function was used, which works for any contractor, as the data is the controlling factor and there are no curve-fitting errors, also, it is more suitable for programming.

The probability of being the lowest bidder according to this model is given by:

$$\text{prob. of winning} = \left[\prod_{r=1}^{N_{key}} (\text{prob. of beating } E_r)\right]\left[\text{prob. of beating } E_{ave}\right]^{N_{ave}}$$

where E_r = the r^{th} key competitor

E_{ave} = an average competitor

N_{key} = number of key comp.

N_{ave} = number of average comp.

Estimation inaccuracies are not taken into account and the true cost is assumed to be the estimated cost.

Morin and Clough do not conclude that a relationship exists between the job cost and the number of competitors, and their computer program results support Gates in this respect.

3.3.8 Whittaker's Model

Whittaker, [8], argues that mathematics cannot supersede judgement entirely and hence some allowance for managerial judgement must be made. His method aims at maximizing the expected profit also. His model assumes that:

1) All bids are drawn from a distribution with a known density function and parameters. There is no knowledge among bidders about the individual bidding behaviour of their competitors.
2) The number of competitors is known.
3) The contract cost is known.

An S-shaped curve was found which fitted the data studied by Whittaker at a 5% level of significance (by χ^2):

$$Y = \theta(0.974449 + 0.1352319F(Y) - 0.005555/F(Y))$$

where Y = bid for contract

$F(Y)$ = cumulative probability distribution

$= \int_{\infty}^{Y} f(b)db$, where $f(b)$ is the density function for a bid of b.

θ = arithmetic mean of competitive bids for the contract and is the parameter the manager must estimate.

It was concluded by Grinyer and Whittaker, [19] that competitors do not vary a lot in their mark-ups for a given tender and, hence, winning the contract depends on the accuracy of the cost estimate. The estimation error was considered to be uniformly distributed about the true tender cost and the profit was calculated by evaluating a break-even mark-up associated with each estimation accuracy and number of competitors. They concluded also that there was no clear relationship between the number of competitors and the job cost.

3.3.9 <u>The Local Market Model (LOMARK)</u>

Wade and Harris, [20], proposed this model by borrowing arguments from various authors and applying them in a local market frame-work. This model uses the complementary probability of winning which is:

(1.0 - probability of losing),

The probability of losing to a specific group of contractors is given by:

(Prob.of losing with A,B,C bidding)=(Prob.of losing to A,B,C)x
(Prob. A.B.C will bid)

To find the probability of success, the competitors bid/own cost ratio is evaluated from the lowest value of A, B or C. This concept of the lowest competitor was used also by the Costain Operational Research Group,[10], and by Hanssmann and Rivett, [21].

The authors of this model agree with Friedman and Park that a relation between the job cost and the number of competitors does exist, but do not specify it, and their study indicates that it is probably not linear.

This method maximizes the expected profit by choosing an optimum mark-up but does not allow for over-heads. However, it does not assume that the bids of competitors are independent and their dependency is implicitly assumed in the method used to generate the probability curve.

3.4 The controversy between Friedman's and Gate's Model

It was seen in the previous section how Friedman's model for evaluating the probability of success assumed that competitors bids are statistically independent which led to the result that the sum of the chances of winning for all competitors does not add up to unity. Several authors criticised Friedman and presented different models, however,the most notable was that due to Gates. The model presented by Gates assumed that competitors bids are dependent but had no mathematical proof. Never-the-less it yields probabilities of success which add up to unity in any given tendering situation which is a true reflection of the actual situation, as one bidder must win the contract. The difference in results obtained by applying both models to a particular bidding case is so large that it cast a shadow of doubt on the validity of all probabilistic bidding models.

Mathew Rosenshine,[22], examined the two models and tried to resolve the controversy. He argues that Gates' model is independent of mark-up. Friedman assumes that competitors randomly select their factors (competitor's bid/own cost estimate) from the Friedman's distribution, while the contractor's own bid factor is fixed at the mark-up he is investigating his chances of success at. In order that Rosenshine's interpretation of Gates' model is correct, i.e. the probability of success is independent of mark-up, the contractor's own bid must be a random selection from the common Friedman's distribution like other competitors. He concludes that both models are correct if interpreted correctly. His explanation of the low success ratio associated with Friedman's model is that it is correct if the contractor choses a mark-up that results in giving him this chance against a competitor.

Rickwood, [10], made an extensive study of this controversy. He concluded that Friedman's model is more accurate when estimation inaccuracies are neglected and bids vary due to mark-up only. On the otherhand Gates' model is more accurate when mark-ups are the same and the variation is due to cost estimates. The Costain Operation Research Group, [10] arrived at the same conclusions also. Rickwood proposed a weighting average of the probability predicted by Friedman or Gates, in which the weighting is relative to the variability in mark-up or estimation.

3.5 Effects of errors in estimation

The true -cost of a job is the cost which would obtain if the job is completed exactly as predicted by the original design and specifications and unforseen conditions and circumstances do not arise. This situation rarely, if ever, applies to civil engineering projects and variations in contract are the rule rather than the exception. Therefore an estimate of the true cost must be made at the stage when the bid is being prepared. The accuracy of this estimate depends on several factors and many of the probabilistic models include some facility to take these errors into consideration. Pim, [23], summarises these errors as follows:

1) Errors of calculation.

2) Errors of quantity in:
   a) Bill items
   b) Rates and standards
   c) Magnitude of over-heads

3) Errors of judgement in:
   a) Planning and method
   b) Assessing learning factor
   c) Estimating non-productive costs
   d) Evaluating economic environment
   e) Guessing the number of competitors
   f) Guessing the attitude of competitors
   g) Assessing penalty of failure

4) Errors of policy in:
   a) Method of application of over-heads
   b) Choice of market

It must be noted that the term error does not mean that a measurement or a judgement is wrong. It only means that abilities and attitudes are different for each competitor. It can be argued that it is partially due to these errors, a successful contractor may end up with a smaller profit than the one implied by his mark-up. This gave rise to the concept of the break-even mark-up investigated by Fine, [24], and Whittaker, [8].

3.5.1 The break-even mark-up

The cost estimate of a contractor can be expressed as:

cost estimate = likely cost ± A%

where A% is the estimation accuracy

and the tender value can be expressed as:

Tender = cost estimate + mark-up.

As the least bid is the winner, the contractor with the highest negative 'A' value is awarded the contract and will end up with a profit less than the one he intended. The average difference between the intended profit and the actual one over a large number of contracts is called the break-even mark-up. The break-even mark-up depend on two factors:

1) The level of estimation accuracy.
2) The number of competitors.

Fine, [24], adopted a simulation technique to evaluate the break-even mark-up. He assumed that all competitors have the same mark-up and constructed tables of the value of M (Estimated cost/Actual cost) obtained from random numbers tables. To correspond with 5%, 10%, and 15% levels of estimation accuracies, the values of M were $.95 < M < 1.05$, $.9 < M < 1.1$, $.85 < M < 1.15$ respectively. The columns of the tables represent the number of bidders which was taken from 2 to 10, and the rows represent the number of contracts they bid for. By examining the minimum M value in each row, i.e. that of the winner, the break-even mark-up corresponding to this number of bidders and accuracy is found.

Whittaker, [8], proposed a mathematical expression for the break-even mark-up as a percentage of estimated cost:

$$BEMU = \frac{100 X Z X n}{n(200-Z)+400}$$

Z = range of estimation accuracy i.e. (if A = ±5%, Z = 10%)

n= number of competitors.

Whittaker assumes in his model that the mark-ups for a given situation do not vary very much between competitors. Therefore, both Fine's and Whittaker's estimations of the break-even mark-up are suitable for models which consider the estimation accuracy as the major factor in determining the probability of winning only. Fig.(5.24) will show the difference between the two approaches in evaluating the break-even mark-up.

3.6 The number of competitors

A very important factor which influences the profit made and the strategy used is the number of competitors. Its accurate estimation is essential as it affects the optimum mark-up for a given situation, as will be seen later.

Some authors (Friedman, Park, Wade and Harris) tried to find a relation between the number of competitors and the job value, while others were unable to arrive at any conclusions. In the OPBID model the total number of competitors was divided into key competitors and other competitors according to their past bidding behaviour. The LOMARK model distinguishes between major competitors and others. The major contractors are the small percentage of firms who have won a major percentage of the jobs in the data analysed by Wade and Harris, [20].

If the number of competitors is unknown, it can be found by making use of a prediction theory. If λ is the best estimate of the number of competitors and assuming it has a Poisson distribution, then the probability of (n) competitors is given by, [25]:

$$P(n) = \frac{\lambda^n e^{-\lambda}}{n!}$$

If Friedman's unknown competitors model is to be used then the probability density function will be:

$$P = \sum_{n=0}^{\infty} P(n).(\text{Probability of beating the typical competitor})^n$$

The distribution can now be used to determine the optimum mark-up.

3.7 The use of feed back information

The use of feed back information can be directed towards improving the present strategy used by a certain contractor regardless of its type. In the methods which will be described in this section, it is not required to know the identity of each competitor, but only their bid values. Following is a description of three of these methods:

A) The first method is proposed by Fine, [23]. The mark-up is increased and decreased by intervals of ½% until 5% on either side. For each increment the number of contracts won is plotted against the new mark-up. If the present mark-up is in the middle of the graph and ½% to 1% variation in mark-up does not result in a significant increase in the number of jobs won, it indicates that the present policy is good. Studying the curve will also give information about the advantages associated with each change of the mark-up.

B) A second method was proposed by, Pim, [23]. The average of all the tenders submitted for a given contract is taken as the true cost and the ratio of each competitors bid to our bid is evaluated. The results are plotted on a curve with the job value on the x-axis and the ratios on the Y-axis. On every job value a line parallel to the Y-axis is drawn and the ratios of the competitors bids to ours are marked on it. The ratio of 1.0 which represents our bid is taken as the datum. Three lines can be drawn; the higher trend line, the lower trend line, and the trend of bidders immediately above the datum. From the first two lines, the effect of the job value on the bidding performance can be studied. The money left on the table by us and its variation with the job is shown by the difference between the third line and the datum. The application of this method is shown in Fig. (3.5).

(C) The method described in (B) does not show the variability of our bid with respect to the job value. Pim, [23], suggested repeating the same procedure but using the average bid as the datum. By drawing our trend line it can be seen how it varies with the job value. The method of regression analysis can be used in drawing the trend lines. The results of the application of this method are shown in Fig. (3.6).

3.8 Survey conclusions:

The previous articles of this chapter have identified the following weaknesses in the existing theories:

1. The difference between the probability of success evaluated by different methods.
2. The different results obtained for the BEMU using Fine's and Whittaker's models.
3. Most of the probabilistic bidding models stem from the concept of maximizing the expected profit but do not consider the contractor's work load.
4. The possibility of the existence, and the type of relation between the job value and the number of competitors.

Therefore a further investigation into these areas is intended in this thesis.

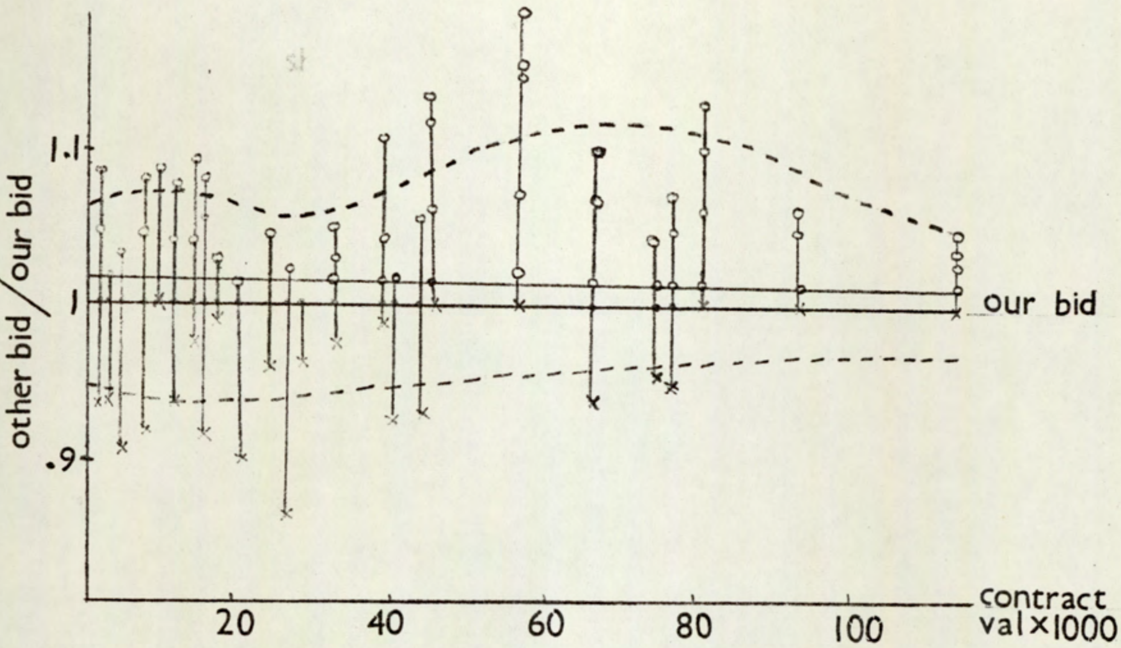

other bid / our bid
1.1
1
.9
our bid
20
40
60
80
100
contract
val×1000

fig. 3.5

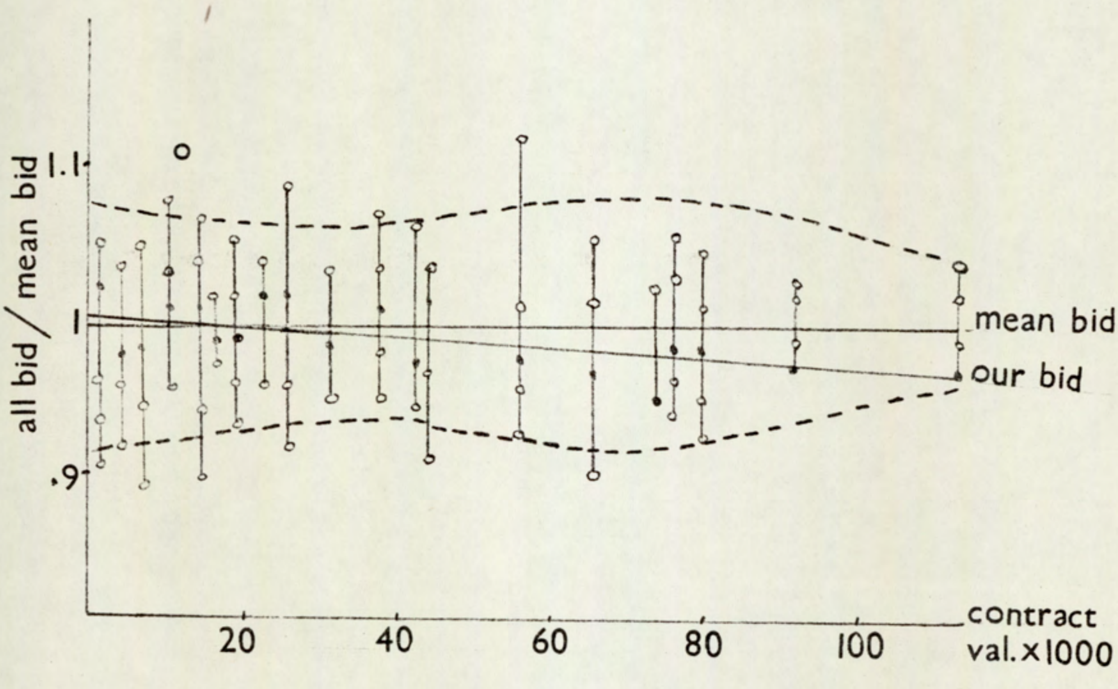

all bid / mean bid
1.1
1
.9
mean bid
our bid
20
40
60
80
100
contract
val.×1000

fig. 3.6

CHAPTER FOUR

ANALYSIS OF DATA SETS

4.1 Introduction

One of the disadvantages of the theory of bidding strategy is that it requires a large volume of correct and relevant bidding data for the building of its models and the application of its various concepts. A known statistical distribution is then fitted to these data sets, which are considered as samples, and the analysis is performed on them. However, such data sets are expensive to prepare, difficult to obtain, and their accuracy is doubtful. During the course of this work, several attempts were made to obtain data sets of actual bidding situations from contractors, but only two sets were finally obtained. Due to the limited amount of information in them and the fact that two sets are not enough, it was not possible to apply and test most of the concepts and models described in the previous chapter. An alternative approach would be to assume a statistical distribution and draw samples from it using simulation techniques. The applications which could not be done on the data sets were tackled using computerised simulation in the next chapter. In the following sections, the available data sets are described and known statistical distributions are fitted to them. A detailed study of the effects of the job value and the application of the concept of maximizing the expected utility value are presented also.

The curve fitting experiments, to the various parameters in the available data sets, were conducted to test if known statistical distribution describes a particular parameter and hence can be used in the future by a contractor to predict the behaviour of this parameter in a particular situation of interest.

A study of an individual contractor's bidding behaviour, with respect to the job value compared to his competitors will be conducted by examining the percentage spread and the average standardised bids. This will illustrate the possibility of improving the success ratio or the achieved profit.

4.2 Description of the data sets.

The two data sets were obtained from two major contracting firms who will be called firm A and firm B. The data set of firm A consists of 24 tenders in the year 1967, 31 in the year 1968, and 21 in the year 1969. For each tender value of firm A, the tender value of the winning bid, the mark-up applied by firm A, and the number of competitors are given. The values of the winning bids are between £5 and £3750k. Firm B's data set consists of the tender of firm B and all its competitors for 47 tenders ranging between £5 and £15000k. The two sets are presented in Appendix (7.3).

4.3 Distributions fitting to data sets

The values, to which a known statistical distribution is to be fitted, are plotted first and a visual fit is attempted. If the plotted values show a similarity to a known distribution then the parameters of this distribution are evaluated and the goodness of fit is checked by methods like the χ^2 test or linear regression and correlation. However, if the plotted values do not indicate any fit with a distribution, the fitting attempt is abandoned.

4.3.1 The tender values of B's set

The grouped frequencies of B's tender values are evaluated in Table (4.1) when plotted against the log of the job value Fig. (4.1) it is seen that the curve does not fit any statistical distribution.

4.3.2 The winning tender value of B's set

A similar attempt was made for the winning bid of each tender in the data set of firm B. The frequencies are presented in Table (4.2) and plotted in Fig.(4.2) which again shows no fit to a statistical distribution.

4.3.3 The winning tender value of A's set

When the frequencies of the winning tenders for this set were evaluated and plotted in a similar way to the previous two sections, they indicated a fit with a normal distribution, Fig.(4.3), the theoretical normal curve being evaluated from Table (4.3). If it is suspected that the distribution is normal, then the goodness of fit can be checked as follows:

TABLE (4.1)

Group No.	Tender value range in k A	B	frequency	log A	log B
1	1 -	2	0	0	.3
2	2 -	5	0	.3	.7
3	5 -	10	2	.7	1.0
4	10 -	25	4	1.0	1.4
5	25 -	50	7	1.4	1.7
6	50 -	100	2	1.7	2.0
7	100 -	200	13	2.0	2.3
8	200 -	500	22	2.3	2.7
9	500 -	1000	28	2.7	3.0
10	1000 -	2000	38	3.0	3.3
11	2000 -	4000	66	3.3	3.6
12	4000 -	8000	56	3.6	3.9
13	8000 -	15000	50	3.9	4.2

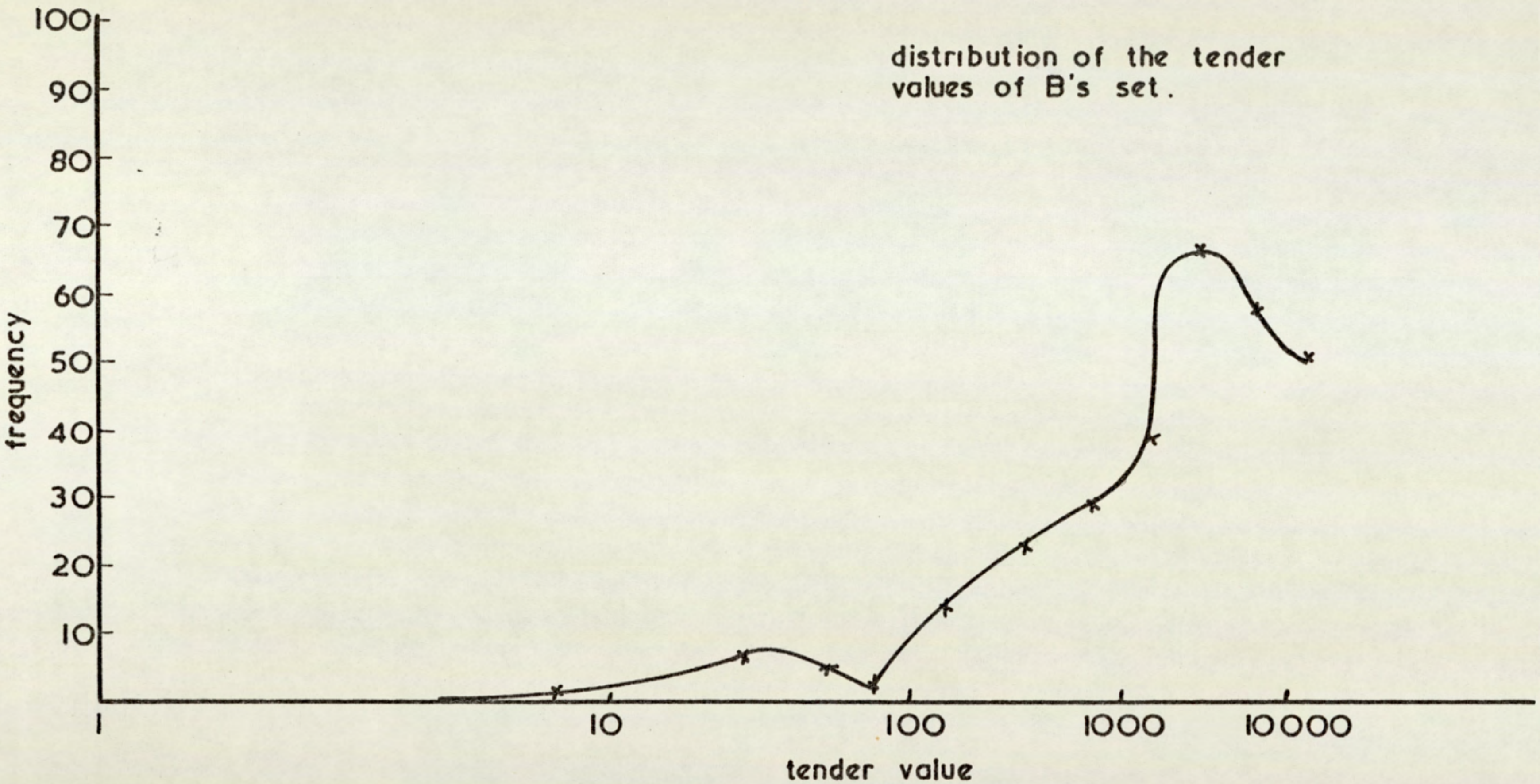

distribution of the tender values of B's set.
frequency
100
90
80
70
60
50
40
30
20
10
1
10
100
1000
10000
tender value

Fig 4.1

TABLE (4.2)

Group No.	Winning tender range in k A - B	frequency	log A	log B
1	1 - 2	0	0	.3
2	2 - 5	0	.3	.7
3	5 - 10	1	.7	1.0
4	10 - 25	1	1.0	1.4
5	25 - 50	0	1.4	1.7
6	50 - 100	1	1.7	2.0
7	100 - 200	2	2.0	2.3
8	200 - 500	5	2.3	2.7
9	500 - 1000	3	2.7	3.0
10	1000 - 2000	10	3.0	3.3
11	2000 - 4000	9	3.3	3.6
12	4000 - 8000	10	3.6	3.9
13	8000 - 15000	7	3.9	4.2

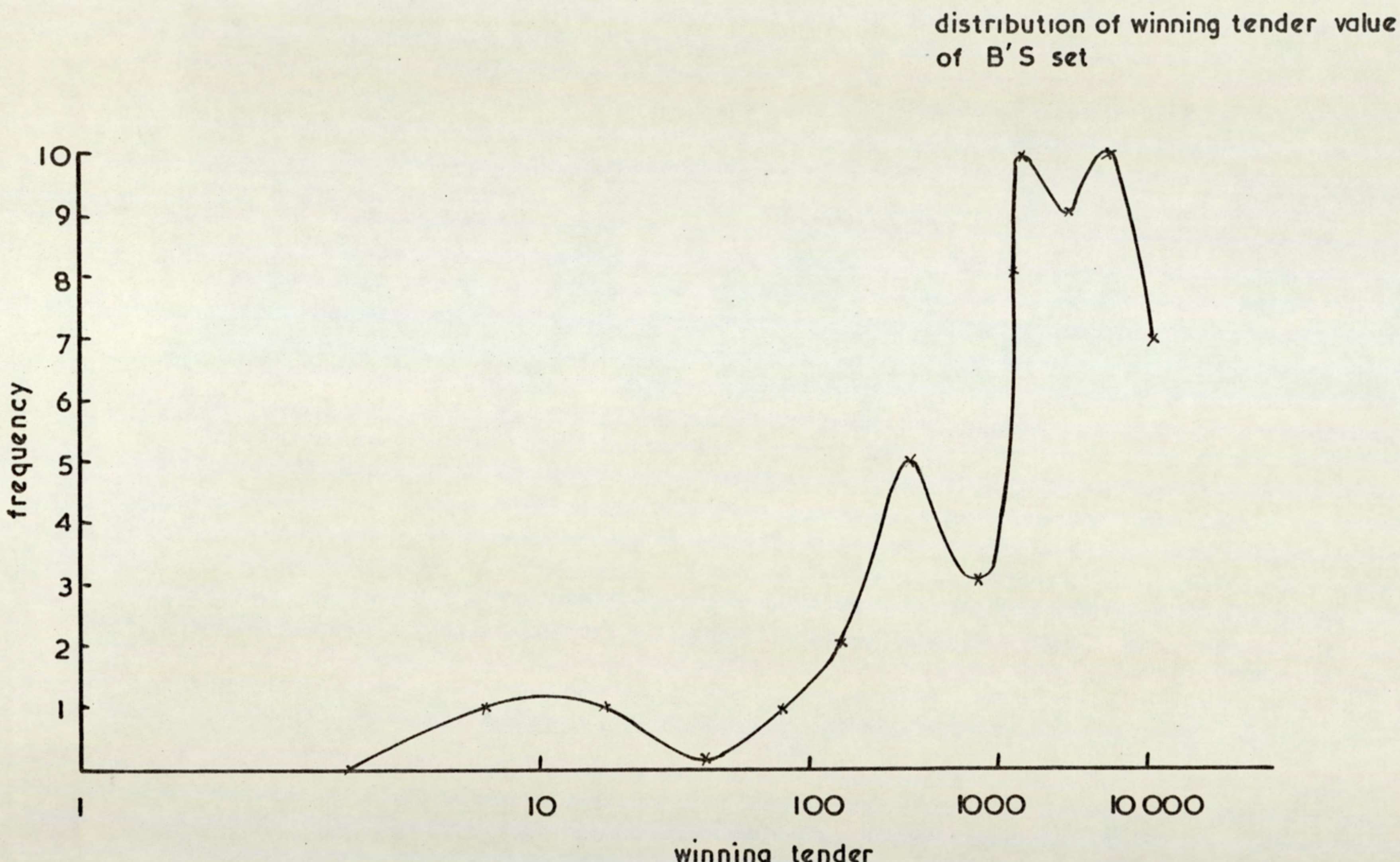

distribution of winning tender value
of B'S set
frequency
10
9
8
7
6
5
4
3
2
1
1
10
100
1000
10 000
winning tender

Fig. 4.2

TABLE (4.3)

Group No.	Winning tender range in k A	B	log.grp. average (x)	freq. (0) (1)	x' (2)	$(x)'^2$ (3)	1x2	1x3	Cum. freq.	Prob. %	$x-\bar{x}$	$u=\frac{x-\bar{x}}{S}$	Ordinate	Expt. freq. (e)	$(0)^2$	$\frac{0^2}{e}$
1	1 -	2	.15	0	0	0	0	0	0	0	-2.20	3.873	0.0002	.0087		
2	2 -	5	.50	0	1	1	0	0	0	0	-1.85	3.257	0.002	.087		
3	5 -	10	.85	1	2	4	2	4	1	1.31	-1.50	2.64	0.012	.530		
4	10 -	25	1.20	4	3	9	12	36	5	6.58	-1.15	2.024	0.0514	2.30	17	5.81
5	25 -	50	1.55	6	4	16	24	96	11	14.47	-0.80	1.408	0.1480	6.6	36	5.45
6	50 -	100	1.85	12	5	25	60	300	23	30.26	-0.50	0.88	0.270	12.11	144	11.89
7	100 -	200	2.15	13	6	36	78	468	36	47.37	-0.20	0.352	0.374	16.75	169	10.09
8	200 -	500	2.50	26	7	49	182	1274	62	81.58	+0.15	0.264	0.3852	17.24	676	39.21
9	500 -	1000	2.85	8	8	64	64	512	70	92.10	+0.50	0.88	0.270	12.11	64	5.28
10	1000 -	2000	3.15	5	9	81	45	405	75	98.68	+0.80	1.408	0.1480	6.6	36	4.04
11	2000 -	4000	3.50	1	10	100	10	100	76	100.0	+1.15	2.024	0.0514	2.3		
Σ				76			477	3195						76.63		81.77

$\bar{x} = 2.35$, $S = 0.568$

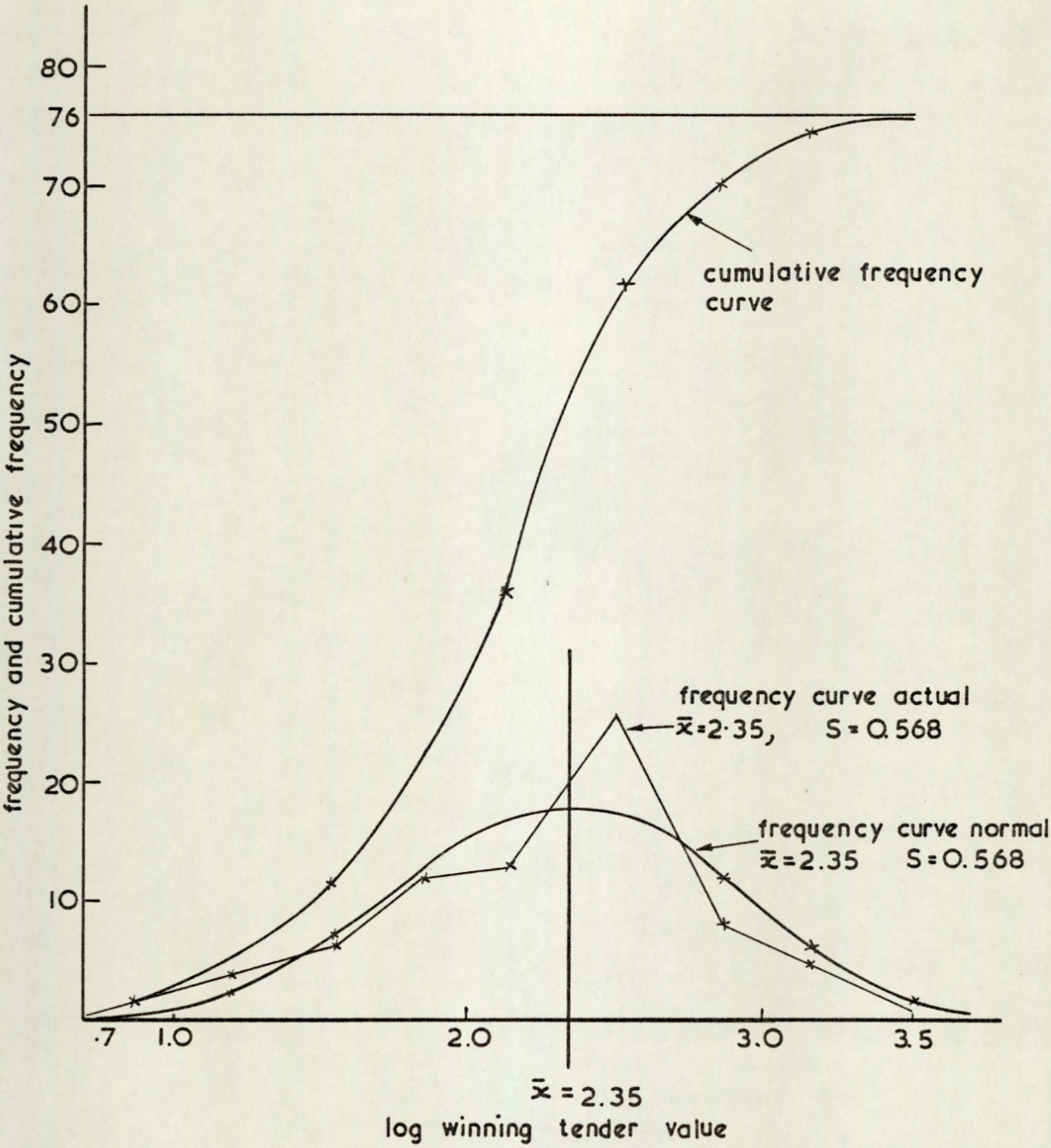

80
76
70
60
50
40
30
20
10
frequency and cumulative frequency
cumulative frequency curve
frequency curve actual
x̄=2·35, S=0.568
frequency curve normal
x̄=2.35 S=0.568
·7
1.0
2.0
3.0
3.5
x̄ = 2.35
log winning tender value

Fig. 4. 3

i) The c.d.f. is determined in terms of percentage probabilities.

ii) These percentages are transformed, for selected values of x, using a table of probits.

iii) If the original distribution is normal, a linear relationship between x and the probit (percentage F(x) should exist, and the goodness of fit can be checked by linear regression and correlation.

An alternative method is the χ^2 test. Both methods were used to check the goodness of fit, and are described subsequently.

A) Probit transformation and linear regression and correlation:

In Fig. (4.4), the probit (y) is plotted against the group average (x) from Table (4.4). A visual check shows good fit with a straight line as the scatter is very little. The goodness of fit with a straight line is checked by linear regression and correlation. With reference to Table (4.4), the coefficient of correlation r is given by:

$$r = \frac{\Sigma xy - \frac{\Sigma x \Sigma y}{n}}{\{[\Sigma x^2 - \frac{(\Sigma x)^2}{n}][\Sigma y^2 - \frac{(\Sigma y)^2}{n}]\}^{\frac{1}{2}}} \tag{4.1}$$

$$= 0.9819$$

TABLE (4.4)

Group No.	Winning tender range in k A		Winning tender range in k B	log.group average (x)	Prob. %	Probit y	xy	x^2	y^2
1	1	-	2	.15	0	0	0	0.022	0
2	2	-	5	.50	0	0	0	0.25	0
3	5	-	10	.85	1.31	2.7	2.29	0.722	7.29
4	10	-	25	1.2	6.58	3.45	4.14	1.44	11.90
5	25	-	50	1.55	14.47	3.94	6.10	2.40	15.52
6	50	-	100	1.85	30.26	4.48	8.29	3.42	20.07
7	100	-	200	2.15	47.37	4.95	10.64	4.62	24.50
8	200	-	500	2.50	81.58	5.92	14.80	6.25	35.04
9	500	-	1000	2.85	92.10	6.43	18.32	8.12	41.34
10	1000	-	2000	3.15	98.86	7.30	22.99	9.92	53.29
11	2000	-	4000	3.50	99.90	8.00	28.31	12.25	65.44
				20.25		47.26	115.89	49.414	274.39

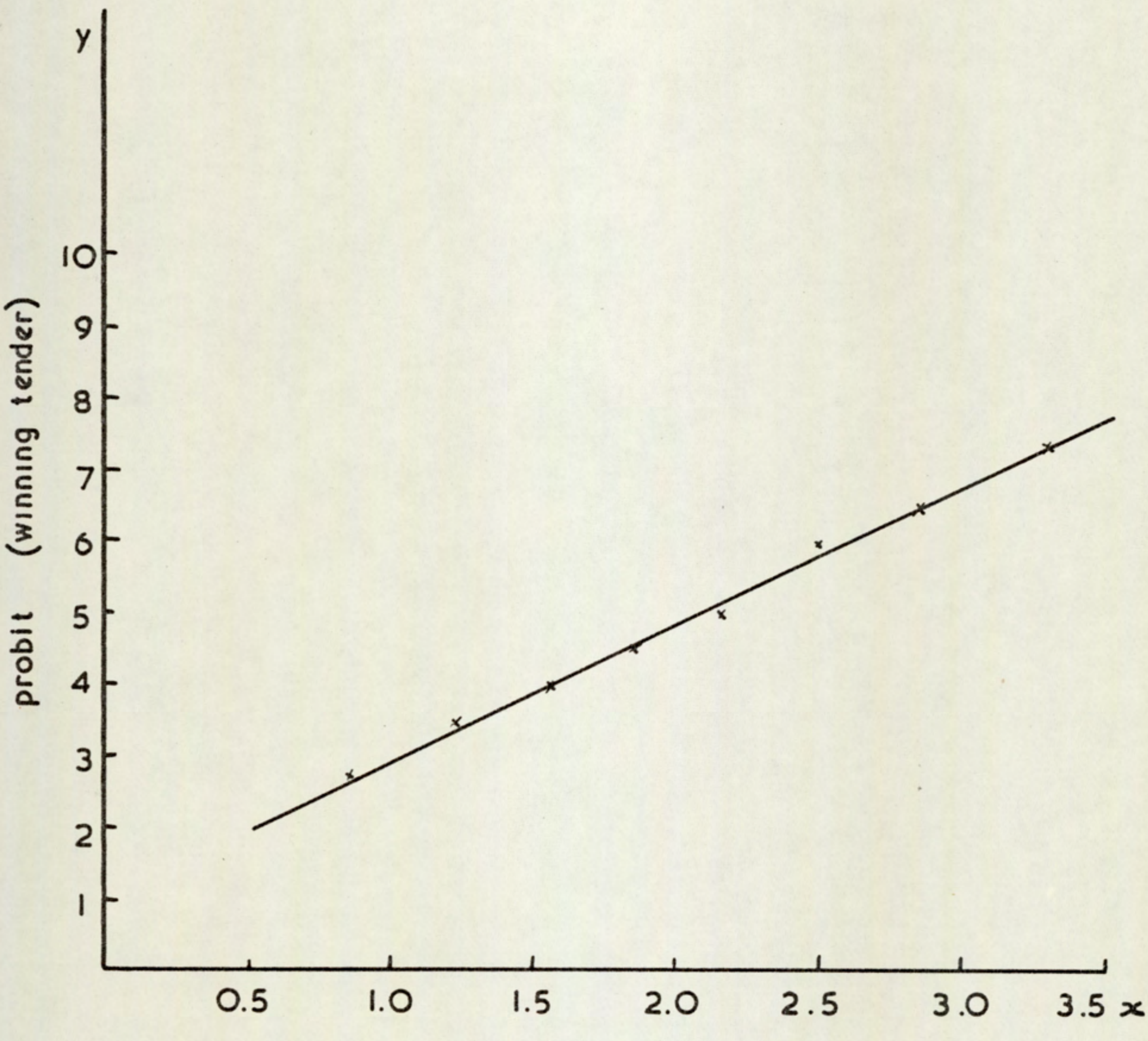

y
10
9
8
7
6
5
4
3
2
1
probit (winning tender)
0.5
1.0
1.5
2.0
2.5
3.0
3.5
x
log group mean

Fig . 4.4

Degrees of freedom = 11 - 2 = 9

For nine degrees of freedom and a 5% level of significance, the coefficient of correlation given in statistical tables is r = 0.6021.

As 0.9818 > 0.6021, the fit is very good and no further analysis of variance is required because the calculated value for r is very close to unity.

B) The χ^2 test: With reference to Table (4.3), the null hypothesis (H_0) is made that the curve fits a normal distribution.

The area under the frequency diagram = (Σfrequency) x group interval

= 76 x 0.335 = 25.46

Expected frequency (e) = Area under the frequency curve x $\frac{\text{ordinate}}{S}$

$$\chi^2 = \Sigma \frac{0^2}{e} - n \quad = 81.77 - 76 = 5.77$$

Number of degrees of freedom = 7 - 2 = 5

For five degrees of freedom and a 5% level of significance, the value of χ^2 given in statistical tables is χ^2 = 11.070

As 11.070 > 5.77, H_0 is accepted.

4.3.4 The net profit of A's set

The mark-ups for most of A's bids are given in the data, otherwise a value of 10% was assumed. A fixed break-even mark-up of 5% was assumed, and the percentage net profit which firm A will achieve, if all its bids are successful, is evaluated and tabulated in

Appendix (7.3). The frequencies of the net profit are plotted in Fig. (4.5), and a visual inspection indicates a fit with a normal distribution.

The goodness of fit was checked in a similar way to section (4.3.3).

A) The probit transformation and linear regression and correlation:

With reference to Table (4.5), the probit (y) is plotted against the group range (x), and a visual fit shows very little scatter as seen in Fig. (4.6). The goodness of fit with the straight line was checked by linear regression and correlation. With reference to Table (4.5) the correlation coefficient r evaluated using equation (4.1) is:

$$r = 0.9986$$

The number of degrees of freedom = 5 - 2 = 3
For 3 degrees of freedom and a 5% level of significance the value of r given in statistical table is r = 0.8783.

As 0.9986 > 0.8783 the fit to a normal distribution is good. Similar to section (4.3.3.(A)) there is no need to do any analysis of variance as the evaluated r value is close to unity.

B) The χ^2 test: The null hypothesis (H_0) that the curve fits a normal distribution is made. With reference to Table (4.6):

$$\chi^2 = \Sigma \frac{0^2}{e} - n = 2.9$$

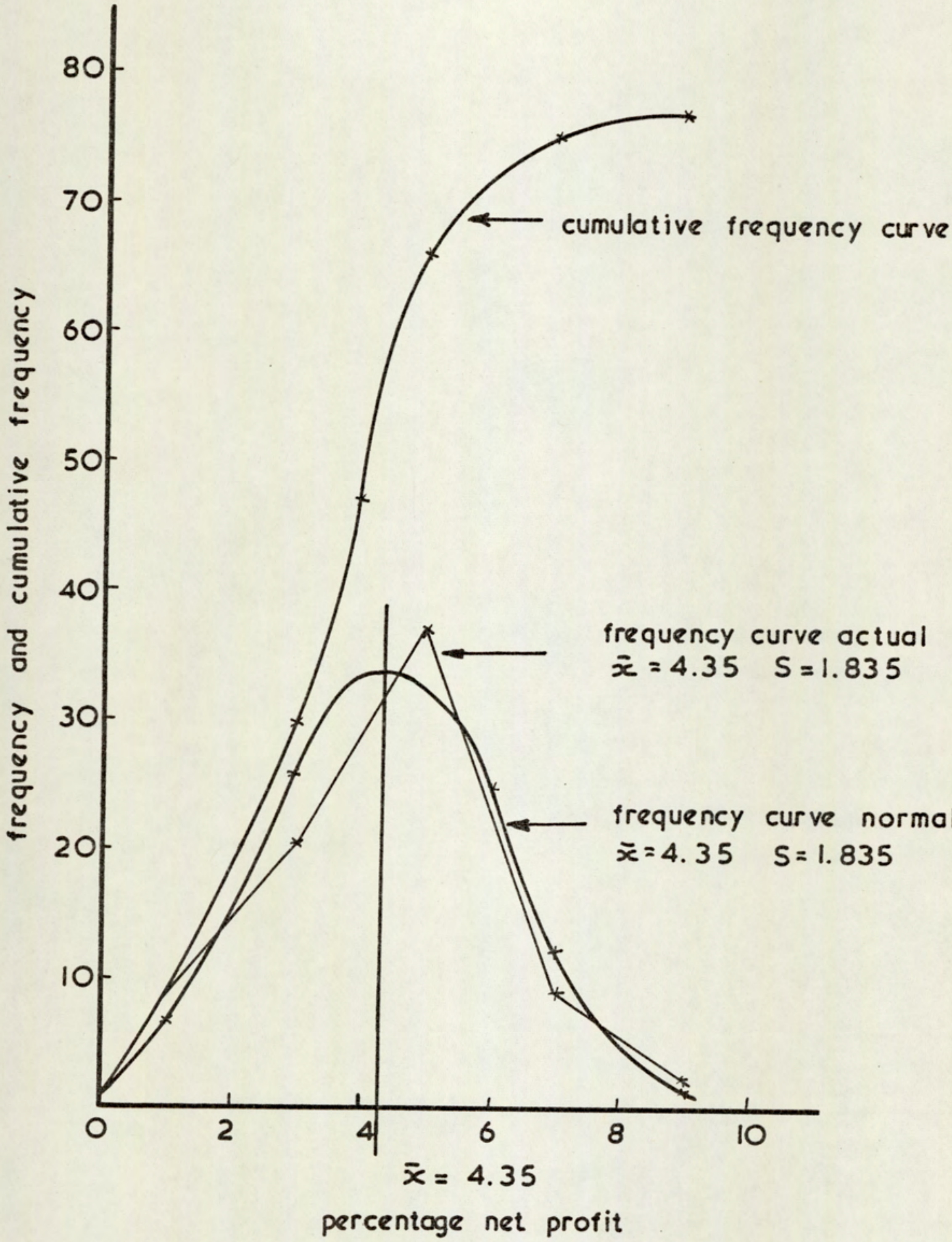
TABLE (4.5)

Group No.	x	Prob. %	Probit y	$x \cdot y$	x^2	y^2
1	1	11.7	3.80	3.80	1	14.44
2	3	37.7	4.69	14.07	9	21.99
3	5	85.7	6.07	30.35	25	36.84
4	7	97.4	6.95	48.65	49	48.30
5	9	100.0	8.10	72.90	81	68.61
Σ	25		29.61	169.77	165	187.18

TABLE (4.6)

Group No.	Group Range	Group Avge (x)	Freq. (0) 1	x' 2	(x'^2) 3	1x2	1x3	Cum. Freq.	Prob. %	$x - \bar{x}$	$u = \frac{x - \bar{x}}{S}$	Ordinate	Expt. Freq.	$(0)^2$	$\frac{0^2}{e}$
1	0 - 2	1	9	0	0	0	0	9	11.7	-3.35	1.82	.0763	6.4	81	12.7
2	2 - 4	3	20	1	1	20	20	29	37.7	-1.35	.74	.3033	25.4	400	15.7
3	4 - 6	5	37	2	4	74	148	66	85.7	+0.65	.35	.3849	32.3	1369	42.4
4	6 - 8	7	9	3	9	27	81	75	97.4	+2.65	1.44	.1416	11.9	121	9.1
5	8 - 10	9	2	4	16	8	32	77	100	+4.65	2.53	.0164	1.4		
Σ			77			129	281						77.4		79.9

$\bar{x} = 4.350, \quad S = 1.835$



80
70
60
50
40
30
20
10
0
2
4
6
8
10
frequency and cumulative frequency
cumulative frequency curve
frequency curve actual
$\bar{x} = 4.35$ S = 1.835
frequency curve normal
$\bar{x} = 4.35$ S = 1.835
$\bar{x} = 4.35$
percentage net profit

Fig. 4.5

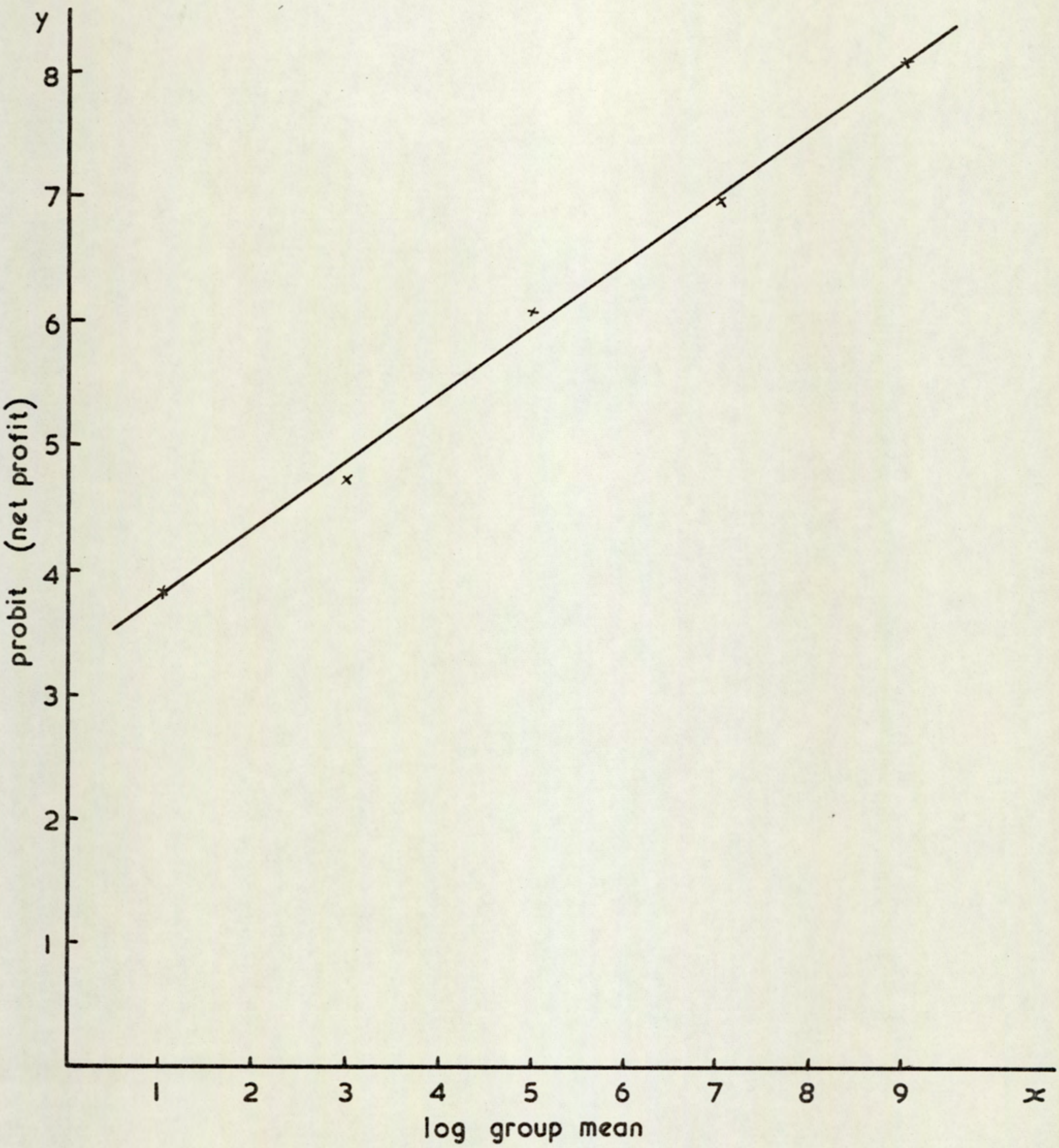


Fig. 4.6

The number of degrees of freedom = 4 - 2 = 2

For 2 degrees of freedom and a 5% level of significance the value of χ^2 given in statistical table is $\chi^2 = 5.991$

As $5.991 > 2.9$ therefore H_o is accepted.

4.3.5 <u>The number of competitors in A's set</u>

The frequencies of the number of competitors for each tender are plotted in Fig. (4.7). It must be noted that a discrete type distribution, only, can fit the number of competitors and the null hypothesis (H_o) that the frequencies fit a Poisson distribution is made:

With reference to Table (4.7) it can be seen that:

$$E(X) = \bar{x} = \frac{689}{76} = 9.06, \qquad V(X) = S^2 = 15.008.$$

It must be noted that for a perfect fit with Poisson's distribution:

$$E(X) = V(X)$$

$$\text{Expected frequency} = 76 \times \frac{e^{-\bar{x}}\,\bar{x}^{x}}{x!}$$

$$\text{and the } \chi^2 = \frac{(0 - e)^2}{e} = 12.37$$

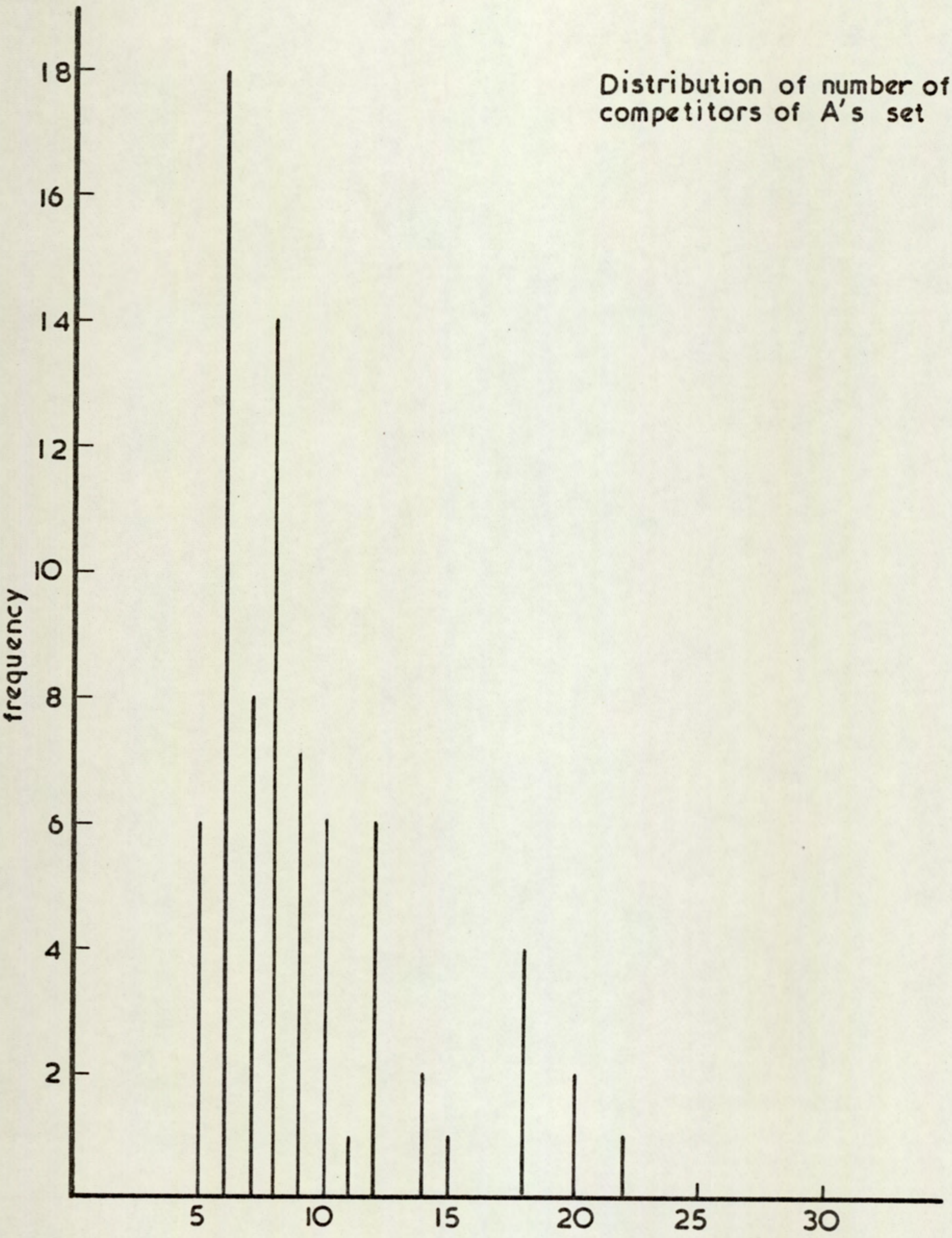
The number of degrees of freedom = 5 - 2 = 3.

For 3 degrees of freedom and a 5% level of significance the value of χ^2 given in statistical tables is $\chi^2 = 7.815$.

As $12.37 > 7.815$ therefore H_o is rejected and the frequencies are considered as not fitting a Poisson distribution.

TABLE (4.7)

Group	No. of competitors (x)	Frequency - 0 -	(freq. x)	x^2	freq. x^2	expected frequency e	$\frac{(0 - e)^2}{e}$
1	3	0	0	9	0	0.177	
2	4	0	0	16	0	1.075	0.49
3	5	6	30	25	150	3.260	
4	6	18	108	36	648	6.58	5.39
5	7	8	56	49	329	9.97	
6	8	14	112	64	896	12.08	0.443
7	9	7	63	81	567	12.20	
8	10	6	60	100	600	10.50	
9	11	1	11	121	121	8.00	4.96
10	12	6	72	144	864	5.39	
11	13	0	0	169	0	3.26	
12	14	2	28	196	392	1.79	
13	15	1	15	225	225	0.908	
14	16	0	0	256	0	0.423	
15	17	0	0	289	0	0.183	1.09
16	18	4	72	324	1296	0.074	
17	19	0	0	361	0	0.028	
18	20	2	40	400	800	0.010	
19	21	0	0	441	0	0.003	
20	22	1	22	484	484	0.001	
		76	689		7372	75.91	12.37



Distribution of number of competitors of A's set
frequency
18
16
14
12
10
8
6
4
2
5
10
15
20
25
30
Number of competitors

Fig 4.7

4.4 The relation between the number of competitors and the job value

It was seen in the previous chapter that Friedman suggested a linear relation between the number of competitors and the job value by assuming that higher job values attract more contractors. Park assumes the relation to be parabolic, Wade and Harris assume that it exists but do not determine it and, finally, Gates and Morin and Clough are inconclusive about the existence of such a relationship. The two sets of data available were used to investigate if a linear relationship, between the number of competitors and the job value, exists by using a logarithmic transformation followed by linear regression and correlation.

4.4.1 Firm A's data set

The job values were grouped logarithmically and the numbers of bidders were also grouped. The results of these groupings are tabulated in Table (4.8), and illustrated in fig. (4.8A) where circles indicate the positions of the group means. However these group means must be weighted by the number of jobs in each group. Note that the extreme value of 39 bidders for one of the jobs has not been included in the tabulation.

The coefficient of linear correlation between the logarithms of the job values (grouped) and the number of bidders (grouped) within each job value range was determined (see Table 4.9A). The number of pairs of observations is 75 therefore for a significant positive correlation at the 5% level the coefficient of correlation (r) would have to exceed 0.2275.

With reference to Table (4.9A) the coefficient of correlation is given by:

$$r = \frac{N\Sigma f u_x u_y - (\Sigma f_x u_x)(\Sigma f_y u_y)}{\sqrt{[N\Sigma f_x u_x^2 - (\Sigma f_x u_x)^2][N\Sigma f_y u_y^2 - (\Sigma f_y u_y)^2]}}$$

$r = 0.12$

Therefore the sample shows no linear correlation.

4.4.2 Firm B's data set:

The job values were grouped logarithmically and the spread of the numbers of bidders is much lower than is the case for A's data set. It is possible that the higher values jobs, apparently preferred by B, are all of the invited tender type whereas in A's case many of the jobs appear to be of the open tendered variety. Table (4.10) and Fig.(4.8B) refer to B's data set.

The coefficient of linear correlation was evaluated similar to (4.4.1) from Table (4.9B). The number of pairs of observations is 47, therefore for a significantlpositive correlation at the 5% level r would have to exceed 0.2817. With reference to Table (4.9B):

$$r = 0.1282$$

Therefore the sample shows no linear correlation.

4.4.3 Comments

Further analysis of the data in order to determine whether certain non-linear correlations existed were not considered worthwhile.

TABLE 4.8

Number of Competitors in Range	3-5	6-8	9-11	12-14	15-17	18-20	21-23	Job Value Range £K	Log job value Average	Number of Jobs in Range	Average number of competitors in job range
Average number of competitors in range	4	7	10	13	16	19	22				
		1						5 - 10	0.85	1	7
	2	1		1				10 - 25	1.20	4	7
	1	2	1	1		1		25 - 50	1.55	6	10
		3	3	2		3		50 - 100	1.85	11	12.2
		8	1			2	1	100 - 200	2.15	12	10.5
	1	16	7	1	1			200 - 500	2.50	26	8.30
	1	5	1	2				500 - 1000	2.85	9	8.3
	1	3		1				1000 - 2000	3.15	5	7.6
		1						2000 - 5000	3.50	1	7
TOTALS	6	40	13	8	1	6	1				

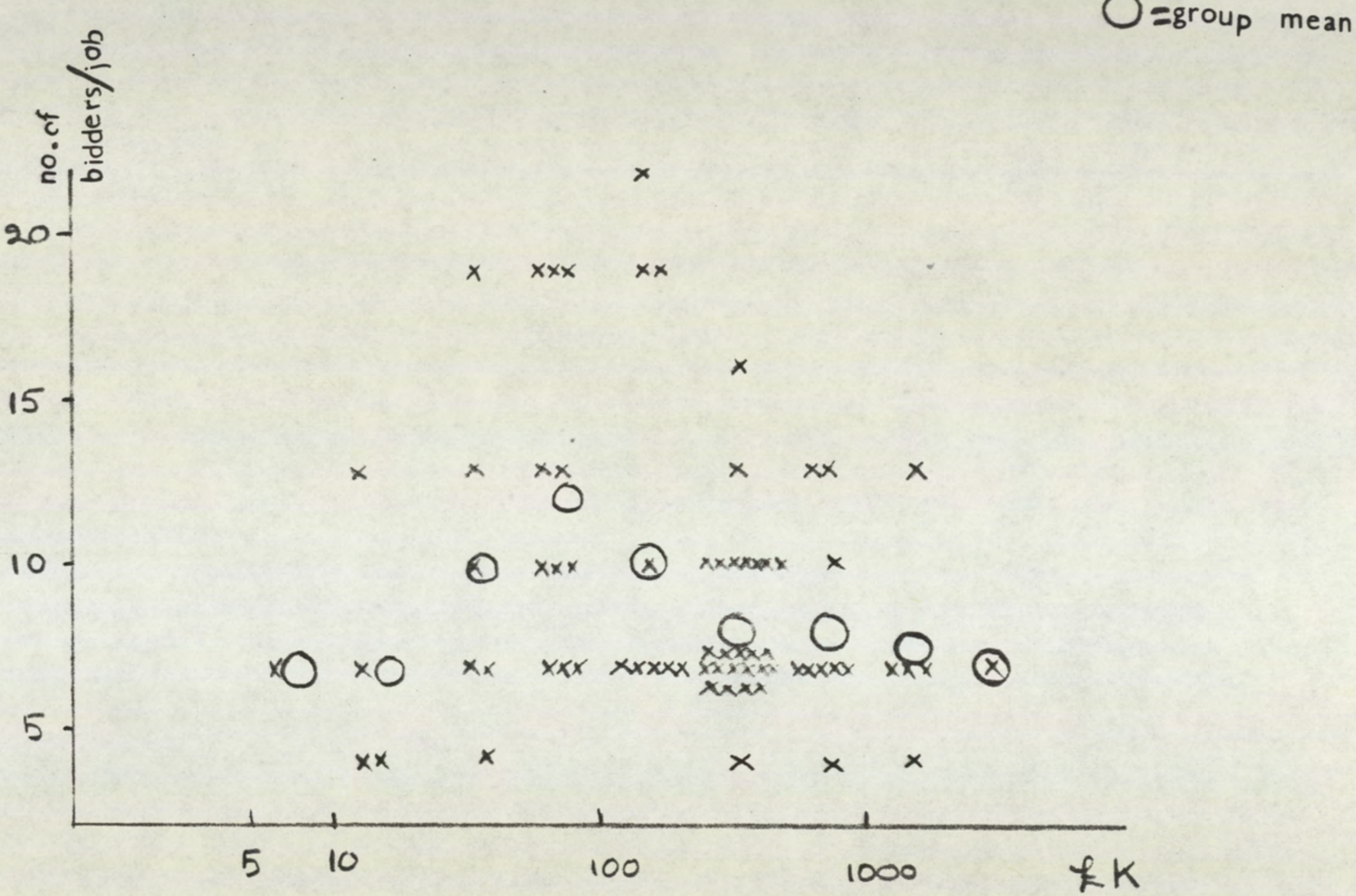


Fig. 4.8A

TABLE 4.9A

u_y \ u_x	-3	-2	-1	0	1	2	3	f_y	$f_y u_y$	$f_y u_y^2$	$fu_x u_y$
4		1 (-8)						1	4	16	-8
3	2 (-18)	1 (-6)		1 (0)				4	12	36	-24
2	1 (-6)	2 (-8)	1 (-2)	1 (0)		1 (4)		6	12	24	-12
1		3 (-6)	3 (-3)	2 (0)		3 (6)		11	11	11	-3
0		8 (0)	1 (0)			2 (0)	1 (0)	12	0	0	
-1	1 (3)	16 (32)	7 (7)	1 (0)	1 (-1)			26	-26	26	41
-2	1 (6)	5 (20)	1 (2)	2 (0)				9	-18	36	28
-3	1 (9)	3 (18)		1 (0)				5	-15	45	27
-4		1 (18)						1	-4	16	8
f_x	6	40	13	8	1	6	1	75	-24	210	57
$f_x u_x$	-18	-80	-13	0	1	12	3	-9.5			
$f_x u_x^2$	54	160	13	0	1	24	9	372			
$fu_x u_y$	-6	50	4	0	-1	10	0	57			

TABLE 4.10

Number of Competitors	4	5	6	7	8	9	Job Value Range £K	No. of jobs in Range	Average number of competitors in range
		1					5 - 10	1	5
					1		10 - 20	1	8
							20 - 50	0	
		1					50 - 100	1	5
			2				100 - 200	2	6
		1	2	2			200 - 500	5	6.2
		1	2				500 - 1000	3	5.7
		2	4	2			1000 - 2000	8	6
	1	4	6	2			2000 - 5000	13	5.7
	1	1	7	2			5000 - 10000	11	5.9
		1	1				10000 - 20000	2	5.5
TOTALS	2	12	24	8	1			47	

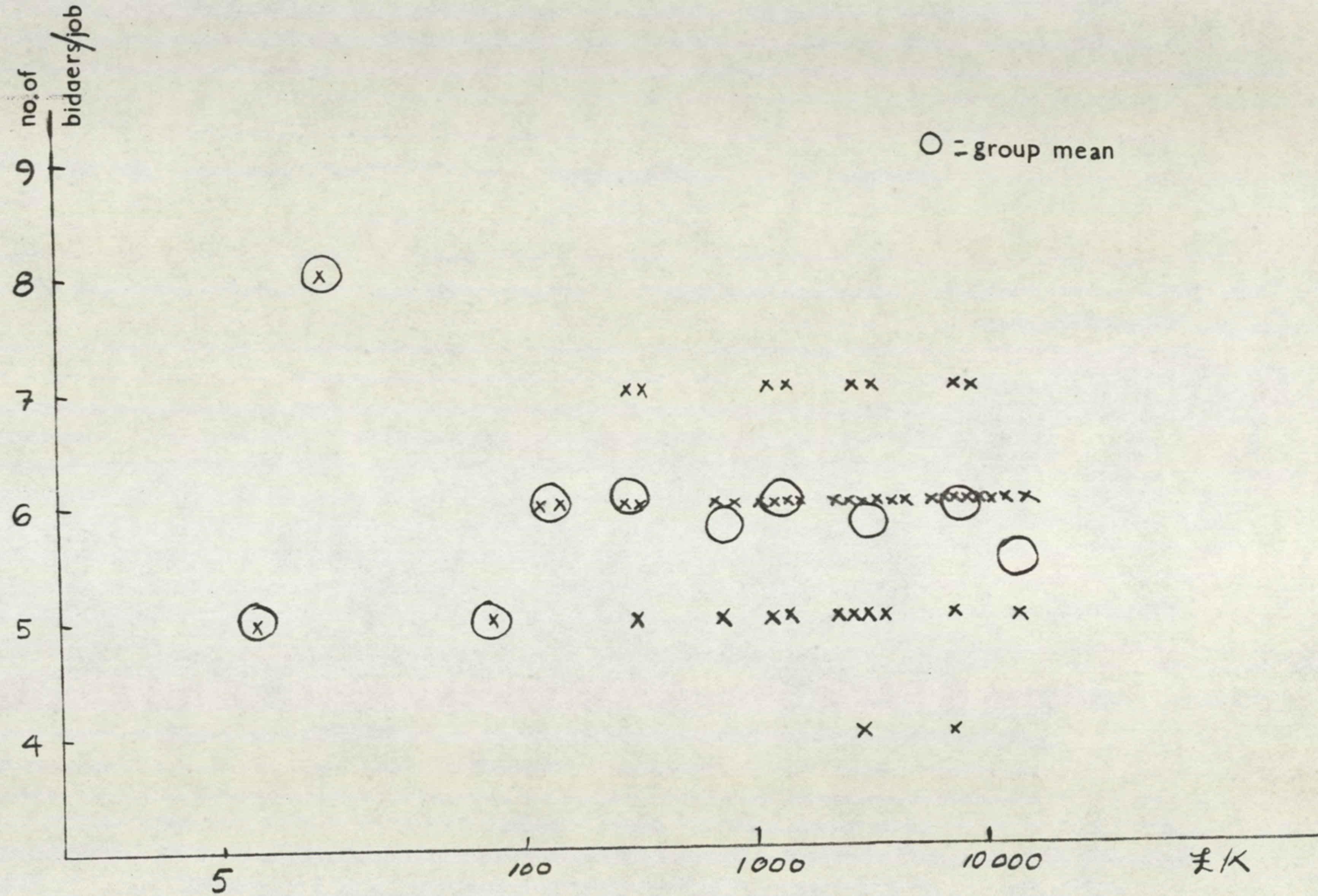


Fig. 4.8 B

TABLE 4.9B

U_y \ U_x	-2	-1	0	1	2	f_y	$f_y\ u_y$	$f_y u_y^2$	$fu_x u_y$
5		1 (-5)				1	5	25	-5
4					1 (8)	1	4	16	8
3						0	0	0	0
2		1 (-2)				1	2	4	-2
1			2 (0)			2	2	2	0
0		1 (0)	2 (0)	2 (0)		5	0	0	0
-1		1 (1)	2 (0)			3	-3	3	1
-2		2 (4)	4 (0)	2 (-4)		8	-16	32	0
-3	1 (6)	4 (12)	6 (0)	2 (-6)		13	-39	117	12
-4	1 (8)	1 (4)	7 (0)	2 (-8)		11	-44	176	4
-5		1 (5)	1 (0)			2	-10	50	5
f_x	2	12	24	8	1	47	-93	425	23
$f_x u_x$	-4	-12	0	8	2	-6			
$f_x u_x^2$	8	12	0	8	4	32			
$fu_x u_y$	14	19	0	-18	8	23			

4.5 Effect of job value on the coefficient of variation

As each bidder assumed his own method in estimating the true tender cost, the value arrived at is obviously not unique. Furthermore the mark-up applied by each bidder is based on his own considerations and hence is a variable also. These factors and several others (e.g. the bidder might not want to win the contract in the first place), are responsible for the wide range in which the bids for a particular contract fall within. The measure of this dispersion can be made by evaluating the mean and the standard deviation of each contract. To include the job value in the picture, it is required to know the relative variability of the bid distribution with respect to the job value expressed as the mean of each contract. A commonly used measure for such cases is the Pearson's coefficient of variation given by,[26],

$$v = \frac{100\ S}{\bar{x}}$$

A computer program which evaluates the mean and standard deviation of each contract in Firm B data set was developed and is presented in Appendix (7.2). The results of the program were used to calculate the coefficients of variation which were plotted against the mean of each contract.

It is not expected to obtain an apparent functional relationship from this graph and hence correlation and regression techniques were applied to find it and test its degree of correlation by the product moment correlation coefficient (r) and the analysis of variance similar to section (4.4.2).

With reference to Table (4.11), it can be seen that:

$$a_1 = \bar{y} = 9.99$$

$$a_2 = \bar{x} = 3.275$$

$$b_1 = -4.560, \quad b_2 = -0.0864$$

$$r = \sqrt{b_1 b_2} = 0.627$$

The number of degrees of freedom = 47-2 = 45.

The value of r for 45 degrees of freedom and a 5% level of significance given in statistical tables is r = 0.2875

As 0.63 > 0.2875 then the correlation is significant at the 5% level.

It was seen that the value of r obtained is significantly smaller than unity and an analysis of variance was conducted to test the correlation.

With reference to Table (4.12),

$$F = \frac{2594.17}{16.74} = 154.96$$

The value of F for the degrees of freedom (2,47) and a 5% level of significance from statistical tables is F = 4.05.

As 154.96 > 4.05 therefore reject (H_0: $\beta_1 = 0$) indicating that the correlation is significant at that level between the job value and the coefficient of variation.

TABLE (4.11)

Ref. No.	Mean in £k	log. mean bid (x)	Std. deviation	Coeff. of var. (y_1)	Percentage Spread (y_2)	x^2	${y_1}^2$	xy_1	${y_2}^2$	xy_2
1	6846	3.83	1310	19.13	3.2	14.71	365.9	73.26	10.24	12.25
2	3745	3.50	480	12.83	12.36	12.77	164.6	44.9	152.76	43.26
3	1516	3.2	91	6.04	4.2	10.11	36.48	19.33	17.64	13.44
4	8371	3.9	893	10.67	10.93	15.38	113.84	41.61	119.46	42.63
5	9890	4.0	630	6.37	5.13	16.0	40.57	25.48	26.32	20.52
6	4148	3.6	353	8.53	9.15	13.08	72.76	30.70	83.72	32.94
7	3653	3.56	211	5.79	9.08	12.67	33.52	20.61	82.44	32.32
8	10506	4.02	568	5.41	2.65	16.16	29.26	21.75	7.02	10.65
9	3604	3.55	369	10.24	7.68	12.65	104.85	36.35	58.98	27.26
10	10501	4.02	739	7.04	4.61	16.17	49.56	28.30	21.25	18.53
11	2937	3.46	240	8.18	5.73	12.02	66.91	28.30	32.83	19.82
12	7257	3.86	359	4.95	2.60	14.90	24.50	19.10	6.76	10.04
13	1800	3.25	99	5.53	8.28	10.59	30.58	17.97	68.55	26.91
14	108	2.03	15	14.55	2.66	4.12	211.70	29.53	7.07	5.4
15	6231	3.8	420	6.74	0.24	14.39	45.43	25.61	0.05	0.91
16	1819	3.25	239	13.17	4.75	10.62	173.44	42.8	22.56	15.44
17	469	2.67	55	11.79	13.95	7.13	139.0	31.48	194.6	37.25
18	4995	3.7	317	6.34	5.78	13.68	40.2	23.46	33.4	21.38
19	11	1.04	3	31.58	78.2	1.08	997.3	32.84	6115.2	81.33
20	9086	3.95	637	7.02	5.96	15.66	49.3	27.72	35.5	23.54
21	2120	3.32	141	6.65	7.50	11.06	44.2	22.08	56.25	24.9
22	6314	3.8	435	6.90	11.85	14.44	47.6	26.22	140.42	45.03
23	184	2.26	26	14.60	9.09	5.13	213.16	33	82.63	20.54
24	1771	3.24	96	5.4	6.98	10.55	29.16	17.5	48.72	22.61
25	4951	3.7	722	14.5	4.61	13.65	210.25	53.65	21.25	17.06
26	12548	4.09	1789	14.2	4.01	16.79	201.64	58.08	16.08	16.4
27	527	2.7	79	15.14	0.52	7.4	229.2	40.87	0.27	1.40
28	314	2.49	36	11.52	3.93	6.23	132.7	28.68	15.44	2.78
29	1171	3.06	124	10.6	6.78	9.42	112.36	32.43	45.96	20.75
30	2139	3.33	103	4.8	6.38	11.09	23.04	15.98	40.7	21.25
31	497	2.7	33	6.78	9.87	7.27	45.97	18.30	97.42	26.65
32	615	2.78	49	8.12	0.76	7.77	65.93	22.57	0.57	2.11
33	165	2.22	12	7.8	1.37	4.91	60.84	17.32	1.87	3.04
34	8488	3.93	804	9.4	4.72	15.43	88.36	36.94	22.28	18.55
35	10978	4.04	963	8.7	4.20	16.32	75.69	35.15	17.64	16.97
36	346	2.54	55	15.9	30.68	6.44	252.81	40.4	941.26	77.93
37	4739	3.67	327	6.92	0.34	13.51	47.88	25.4	0.115	1.25
38	670	2.82	69	10.35	5.25	7.98	107.12	29.2	27.56	14.80
39	4603	3.66	401	8.73	0.38	13.42	76.21	31.95	0.144	1.4
40	2354	3.37	137	5.84	3.61	11.37	34.10	19.68	13.03	12.16
41	3784	3.58	218	5.78	0.92	12.8	33.4	20.7	0.85	3.29
42	26	1.41	6	23.12	30.83	2.0	534.53	32.6	950.5	43.47
43	758	2.88	102	13.56	7.97	8.3	183.87	39.05	63.5	22.95
44	2257	3.35	168	7.45	2.57	11.25	55.50	24.95	6.6	8.6
45	4206	3.62	265	6.32	5.45	13.13	39.94	22.87	29.70	19.73
46	1566	3.19	206	13.17	6.95	10.20	173.45	42.01	48.30	22.17
47	10453	4.02	602	5.76	2.84	16.15	33.17	23.15	8.06	11.42
Σ		153.96		469.91	377.5	527.9	5941.78	1431.83	9793.47	1002.8

TABLE (4.12)

Source of variation	Degree of freedom	Sum of squares	Mean squares	F
Total	47	5941.78		
$R(\beta_o)$	1	4698.2		
$R(\beta_1/\beta_o)$	1	490.14	2594.17	154.96
Error	45	753.43	16.74	

The regression lines are, with reference to Table (4.11),

$$Y = 24.92 - 4.56\ X$$

$$X = 4.13 - 0.0864\ Y,$$ and are drawn in Fig. (4.9).

The type of relationship given by the correlation lines of Fig. (4.9), is thought to be due to the fact that small contractors with low over-heads bid for contracts with a low job value together with larger contractors operating at the lower end of their market and submitting bids based on an over-estimation of the true cost due to their inexperience in this field. While contracts with high job values are tendered for by experienced contractors specialized in the particular field and taking more care in their estimations due to the high element of risk involved. Another reason for the high variation in the low job value range, is that a small difference in the estimates of competitor will represent a high percentage of the overall cost. While for high job value contracts the small variations are insignificant with respect to the job cost estimate.

These results can very well be a special case for this particular set of data. McCaffer, by studying (185) bids for building work contracts, concludes that there is no correlation between the job value and the coefficient of variation, [26]. A study of a large number of data sets is required to establish if such a relationship exists.

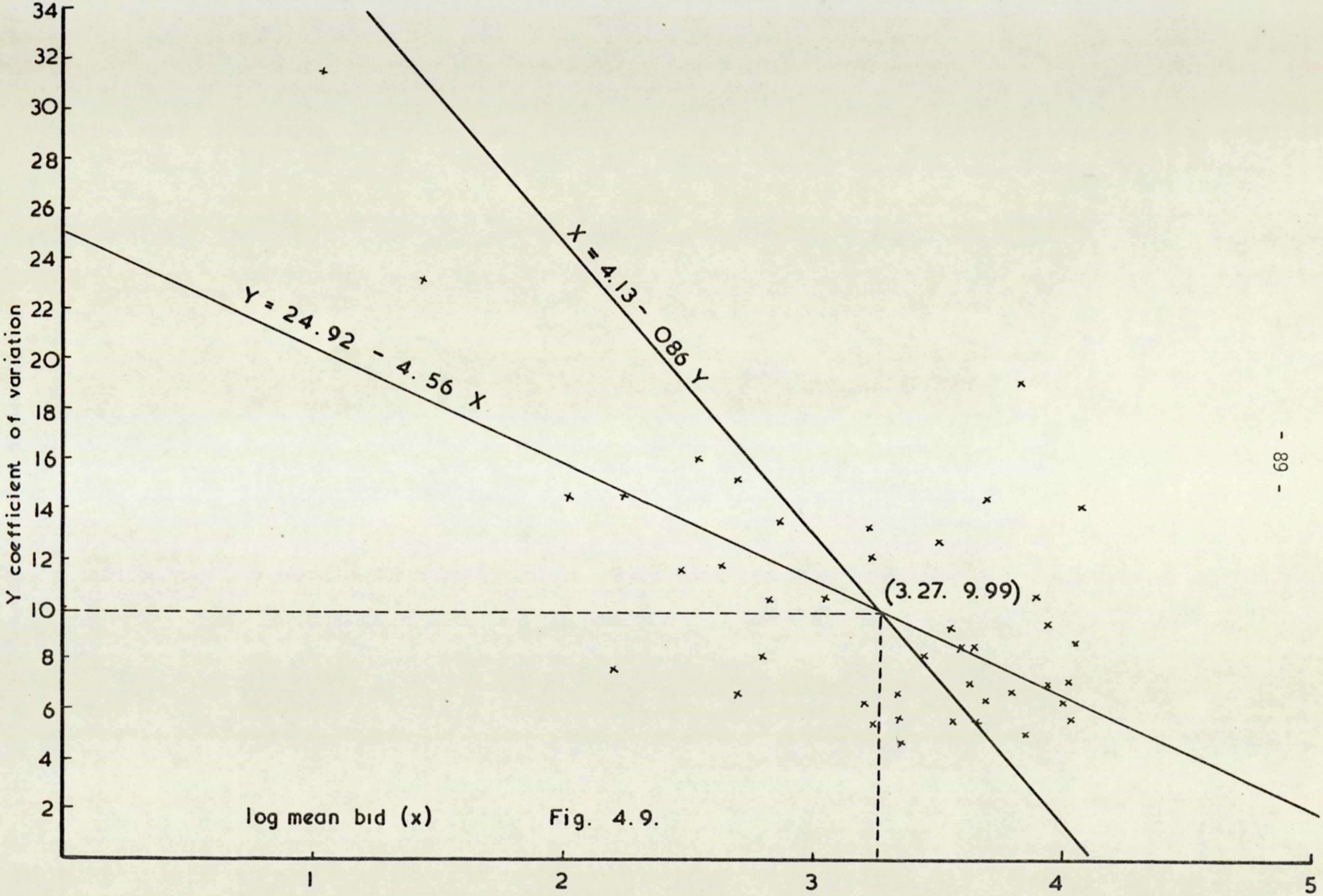

Y coefficient of variation
log mean bid (x)
Y = 24.92 - 4.56 X
X = 4.13 - .086 Y
(3.27. 9.99)
34
32
30
28
26
24
22
20
18
16
14
12
10
8
6
4
2
1
2
3
4
5

Fig. 4.9.

4.6 Effects of the job value on the percentage spread

The percentage spread is defined as:

$$\frac{\text{second lowest bid - lowest bid}}{\text{lowest bid}} \times 100$$

The values for the percentage spread were calculated for all contracts of firm B data set, and a study similar to that of section (4.5) was conducted.

With reference to Table (4.11), it can be seen that

$$a_1 = \bar{y} = 8.03$$

$$a_2 = \bar{x} = 3.275$$

$$b_1 = -9.92, \quad b_2 = -0.0345$$

$$r = \sqrt{b_1 b_2} = 0.585$$

The number of degrees of freedom = 47 - 2 = 45

The value of r for 45 degrees of freedom and a 5% level of significance given in statistical tables is r = 0.2875.

As 0.585 > 0.2895 therefore the correlation is significant at the 5% level.

It was seen that the value of r obtained is significantly smaller than unity and an analysis of variance was conducted to test the correlation.

With reference to Table (4.13)

$$F = \frac{2675.57}{98.717} = 27.10$$

The value of F for the degrees of freedom (2, 47) and 5% level of significance from statistical tables is F = 4.05.

As 27.10 > 4.05 therefore reject (H_0: $\beta_1 = 0$) indicating that the correlation is significant at that level between the job value and the percentage spread.

The regression lines are with reference to Table (4.11),

$$Y = 40.51 - 9.92\ X$$

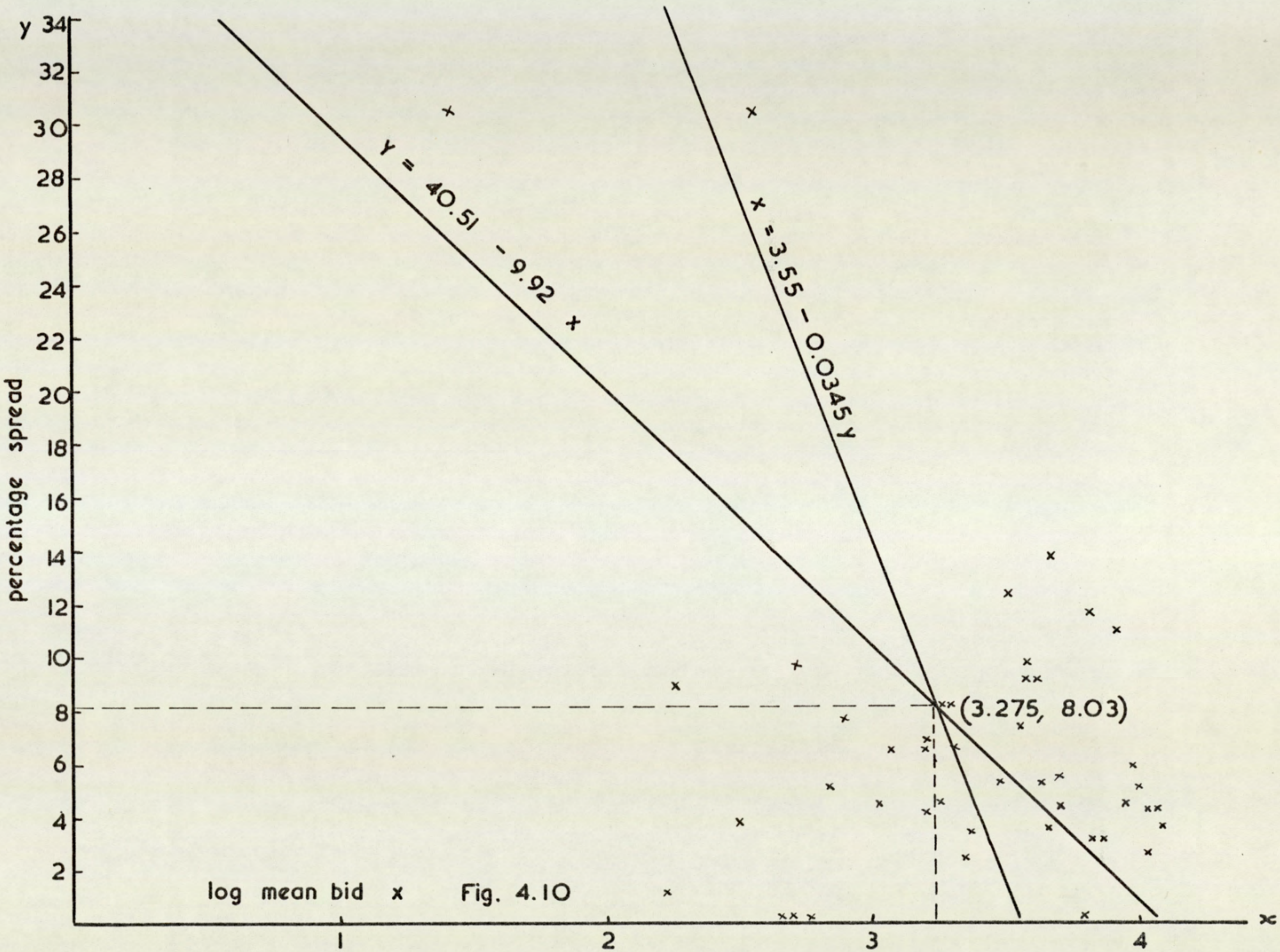
$$X = 3.55 - 0.0345\ Y$$

and are drawn in Fig. (4.10).

It can be seen that there is a negative correlation between the job value and percentage spread. The slope of the line is greater than that of the coefficient of variation indicating that at the low job value side there is a lot of money left on the table but it decreases rapidly as the job value is increased. This again can be due to the lack of care and inexperience in estimation for contracts with low job values which is not tolerated at the high job value end.

TABLE (4.13)

Source of variation	Degree of freedom	Sum of squares	Mean squares	F
Total	47	9793.47		
$R(\beta_o)$	1	3032.04		
$R(\beta_1/\beta_o)$	1	2319.11	2675.57	27.10
Error	45	4442.3	98.717	



log mean bid x Fig. 4.10

4.7 The effect of job value on average standardised bids

An average standardised bid is calculated by dividing the original bid by the mean of all bids for a given contract. This value can be used in examining the behaviour of a certain competitor and that of all the competitors as well. McCaffer, [26], suggests listing the average of these values of several bids for any competitor and check to see if that competitor normally bids below, above, or near the mean. Also, if the average of all competitors is close to unity, it means that their behaviour is consistent, or similar, in estimating and marking-up tenders. However, the identities of the competitors are not known in firm B's data set, and the values obtained for the average standardised bids of competitors have a much larger spread than that seen in McCaffer's data and therefore there is no indication that their policies are similar.

Another approach which makes use of the average standardised bid, and relates it to job value, is that suggested by Pim, [23], and discussed in section (3.7). In this approach, the values of the average standardised bids, including that of firm B in its data set for each contract, are plotted on a vertical line at the mean of each particular contract. Trend lines of the highest and lowest bid can be drawn and their variation with the job value can be studied. The bids of a contractor can either be strung out along the graph, in which case it is concluded that his strategy is not consistent, or they show a definite trend with respect to the job value. An imaginery bid can be plotted on each vertical line which is:

$$\frac{\text{mean - 2 standard deviation}}{\text{mean}}$$

This is an imaginary minimum bid whose trend can be studied with respect to the job value also.

Fig. (4.11) shows that the trend lines for the maximum and minimum bid are symmetric with respect to the datum, which is in this case the mean bid, and they come down closer to each other as the job value increases. This indicates again the extra care taken in bidding for high job value contracts. Firm B's bid trend shows very good correlation with the mean for intermediate and high job value contracts but some fluctuation is observed at the lower end which could be the result of two factors. The first is that firm B may be bidding in an area where they are not experienced and entered in because of market circumstances. The second reason is that a large number of inexperienced competitors bid for small job value contracts thus distorting the mean away from good estimates.

Another way of displaying these results was suggested by Pim also in which the datum line is taken as firm B's bid and the remaining bids for each contract are expressed as fractions or multiples of it. Maximum and minimum bid trends can also be drawn and they were found to be similar to those obtained when the datum was the mean bid, [23]. However, the advantage of this method is that a line may be drawn through the points representing the bids of the contractor immediately above the datum and the difference between this line and the datum will represent the amount that firm B's mark-up can be increased without affecting the order of the bids. This difference was found to be very small in the present set of data and, hence, not justifying the drawing of this line. The display of the result, using this approach is presented in Fig. (4.12).

Fig. 4.11

Fig. 4.12

4.8 Application of the concept of expected utility value

A method proposed by Mr. Bulman of Tarmac, [27] enables each company to reflect its policy towards profits and losses on the mark-up chosen for its tenders. It uses the utility curve, which assigns a value on an arbitrary scale between 0 and 1 to any profit or loss the company might achieve. If it is a straight line it will indicate that both losses and gains are treated similarly. However, if large losses are to be avoided more firmly than large profits, the proposed curve is shown in Fig. (4.13).

4.8.1 Method of Analysis

The proposed method was applied to firm B's data set. The mean of each tender was evaluated and the variation with respect to it, of each bid was found. A histogram of the cumulative variations, with respect to the mean, is plotted in Fig. (4.14) which indicates a possible fit with a normal distribution. The goodness of fit was tested by logarithmic transformation followed by linear regression and correlation. With reference to Table (4.14) it can be seen that:

$$a_1 = \bar{y} = 5.494$$

$$a_2 = \bar{x} = 1.025$$

$$b_1 = 11.965, \quad b_2 = .083$$

$$r = \sqrt{b_1 b_2} = 0.9965$$

The number of degrees of freedom = 9 - 2 = 7

The value of r for 7 degrees of freedom and a 5% level of significance given in statistical tables is r = 0.6664.

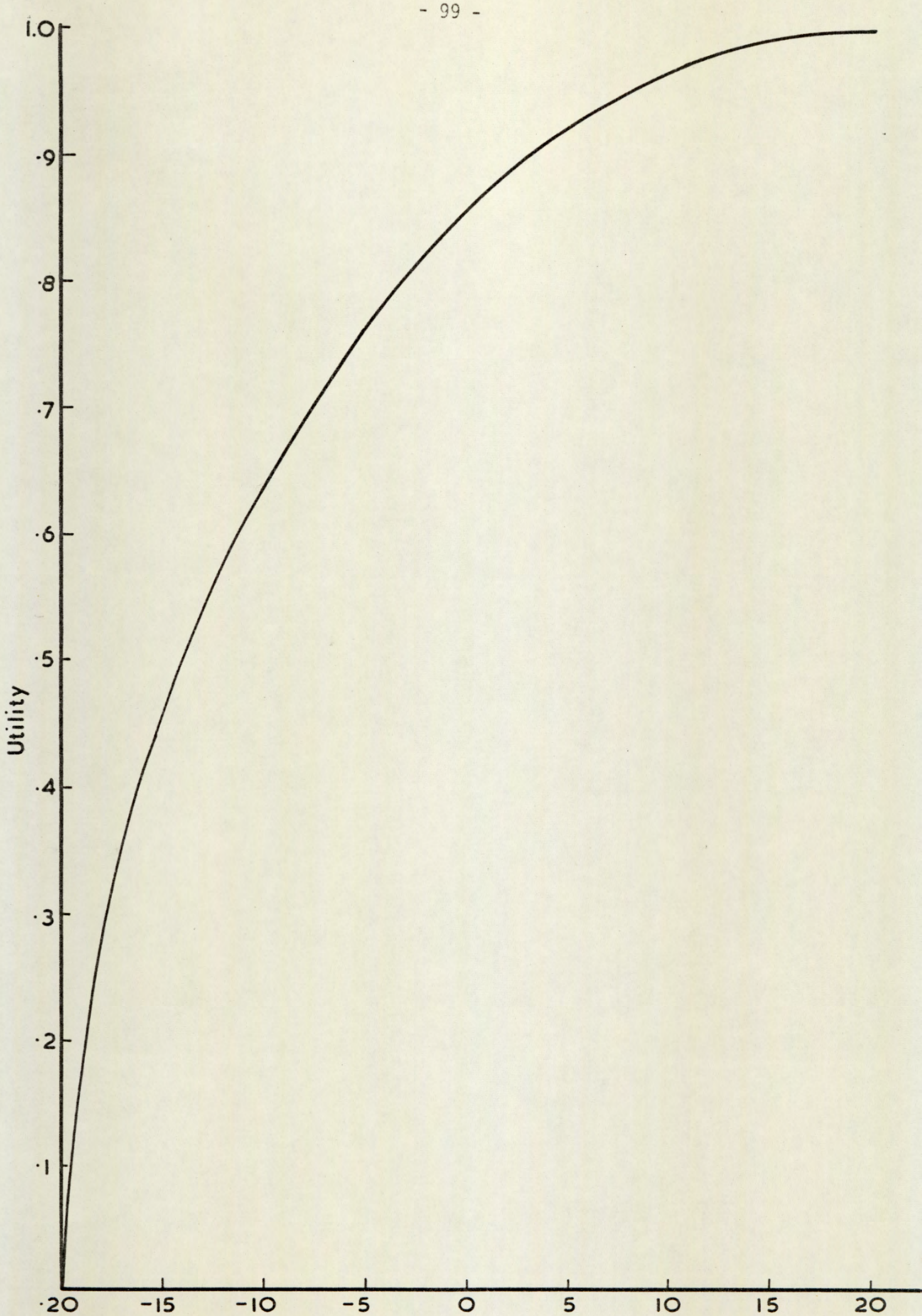
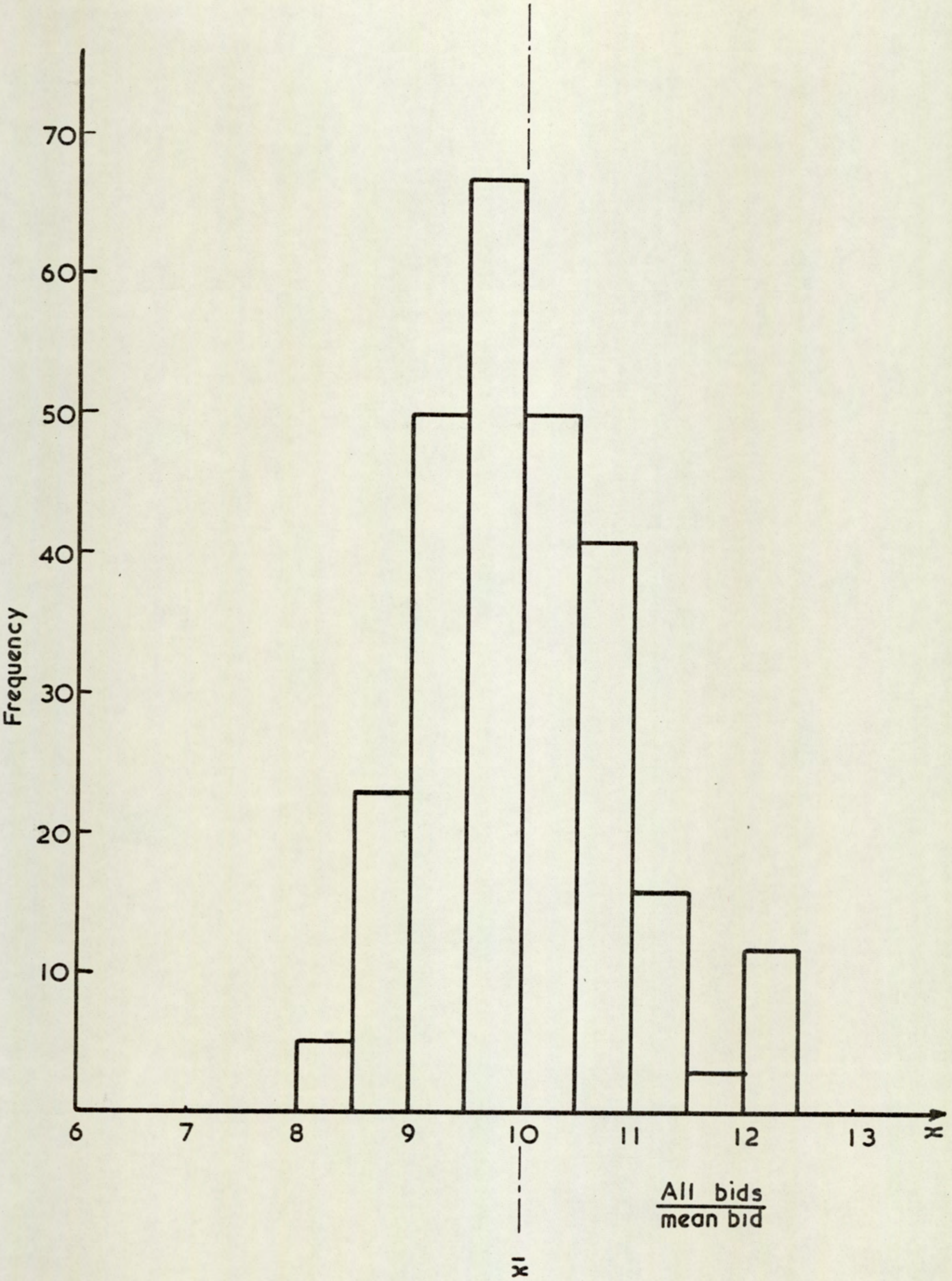

1.0
·9
·8
·7
·6
·5
·4
·3
·2
·1
Utility
·20
-15
-10
-5
0
5
10
15
20
Average percentage gain

Fig. 4.13



70
60
50
40
30
20
10
Frequency
6
7
8
9
10
11
12
13
x
All bids
mean bid
x̄

Fig. 4.14

TABLE (4.14)

Group No.	Group range	Group average x	freq.	Cumulative frequency	Prob. %	Probit y	x^2	y^2	xy
1	.8 - .85	.825	5	5	1.87	2.80	.68	7.84	2.31
2	.85 - .90	.875	23	28	10.49	3.95	.765	15.6	3.456
3	.90 - .95	.925	50	78	29.21	4.45	.855	19.8	4.116
4	.95 - 1.0	.975	67	145	54.30	5.11	.950	26.11	4.98
5	1.0 - 1.05	1.025	50	195	73.03	5.61	1.05	31.47	5.75
6	1.05 - 1.10	1.075	41	236	88.39	6.18	1.155	38.19	6.64
7	1.10 - 1.15	1.125	16	252	94.38	6.55	1.265	42.9	7.368
8	1.15 - 1.20	1.175	3	255	25.50	6.70	1.38	44.89	7.87
9	1.20 - 1.25	1.225	12	267	100.0	8.10	1.50	65.61	9.992
Σ		9.225	267			49.45	9.6	292.41	52.4

As 0.9965 > 0.6664 therefore the correlation is significant at the 5% level.

The evaluation of the mean and standard deviation for this distribution is shown in Table (4.15).

Grinyer and Whittaker, [19], suggest that mark-ups do not vary greatly between firms, and in 159 contracts studied by them the mark-ups variation was within ±0.35% of a mark-up mean of 6.8%,, which is very small. If this argument is applied to the distribution obtained in this study it may be said that the distribution represents estimated cost as well as tender values. By using the area under the normal curve from statistical tables it is possible to determine the probability of winning associated with each particular deviation from the mean.

A hypothetical contractor is assumed to have estimates generally 10% below the mean. A mark-up of 1% to 8% is applied to his estimates from which table (4.16) is constructed. Column 1 is the mark-up and column 2 is the probability of winning associated with it, obtained from tables as discussed earlier. Across the top of the following 5 columns the probabilities of errors and their values are shown. They are obtained by assuming the error to be normally distributed. The four rows for each mark-up are as follows:

1. Gross percentage gain: the error value + mark-up
2. Average percentage gain: row(1) x probability of success

3. Utility: the utility factor between 0 and 1 corresponding to row (2).
4. Weighted utility: row(3) x probability of error.

The mark-up with the highest utility is the one with the highest total weighted utilities.

From Table (4.16) it is seen that the optimum mark-up is 6%. This result compares well with that obtained by computerised simulation which will be presented in the next chapter. The advantage of this method is that it does not assign an estimation accuracy value.

TABLE (4.15)

Group No.	Group range	Group Average	freq.	x'	freq.x'	x'^2	freq.x'^2
1	.8 - .85	.825	5	0	0	0	0
2	.85 - .90	.875	23	1	23	1	23
3	.90 - .95	.925	50	2	100	4	200
4	.95 - 1.0	.975	67	3	201	9	603
5	1.0 - 1.05	1.025	50	4	200	16	800
6	1.05 - 1.10	1.075	41	5	205	25	1025
7	1.10 - 1.15	1.125	16	6	96	36	576
8	1.15 - 1.20	1.175	3	7	21	49	147
9	1.20 - 1.25	1.225	12	8	96	64	768
Σ			267		942		4142

$\bar{x} = 1.001$

S = Std.dev. = .087

TABLE (4.16)

Mark up	Prob. of succ.	Probability of error	.05	.27	.36	.27	.05	Total W. Utility
		error	+16	+4	0	-4	-16	
		1.Gross % gain	16.1	4.1	0.1	-3.9	-15.9	
		2.Av. % gain	11.75	2.99	0.073	-2.84	-11.6	
.1	.73	3.Utility	.98	.92	0.88	.82	.59	
		4.W.Utility	.05	.24	0.31	.22	.029	.849
		1.Gross % gain	16.2	4.2	0.2	-3.8	-15.8	
		2. Av. % gain	11.34	2.94	.14	-2.66	-11.06	
.2	.7	3.Utility	0.97	0.91	.9	.83	0.6	
		4.W. Utility	0.048	0.24	.32	.22	0.03	.858
		1.Gross % gain	16.3	4.3	.3	-3.7	-15.7	
		2. Av. % gain	10.75	2.83	.198	-2.44	-10.36	
.3	.66	3.Utility	.28	.91	0.89	.84	.63	
		4.W.Utility	.05	.24	.32	.22	.03	.860
		1.Gross % gain	16.4	4.4	.4	-3.6	-15.6	
		2.Av. % gain	8.03	2.15	.19	-1.76	-7.63	
.4	.49	3.Utility	.96	0.91	.89	.85	.7	
		4.W.Utility	.048	.24	.32	.229	.035	.872
		1.Gross % gain	16.5	4.5	.5	-3.5	-15.5	
		2.Av. % gain	7.09	1.93	.21	-1.5	-6.66	
.5	.43	3. Utility	.95	.9	.89	.85	.75	
		4.W. Utility	.47	.24	.32	.229	.037	.873
		1.Gross % gain	16.6	4.6	.6	-3.4	-15.4	
		2.Av.% gain	6.14	1.7	.22	-1.25	-5.69	
.6	.37	3.Utility	.94	0.9	.89	.86	.77	
		4.W. Utility	.047	.24	.32	.23	.038	.875
		1.Gross % gain	16.7	4.7	.7	-3.3	-15.3	
		2.Av. % gain	5.17	1.45	.21	-1.02	-4.74	
.7	.31	3.Utility	.925	.885	.88	.87	.79	
		4.W. Utility	.046	.238	.316	.235	.039	.874
		1.Gross % gain	16.8	4.8	.8	-3.2	-15.2	
		2.Av. % gain	4.2	1.2	.2	-0.8	-3.8	
.8	.25	3.Utility	.92	.885	.88	.85	.8	
		4.W. Utility	.046	.238	.316	.229	.04	.869

CHAPTER FIVE

COMPUTERISED SIMULATION

5.1 Testing the simulation program

A computerised simulation program was developed by Armstrong,[28], to investigate the effects of improving the estimation accuracies (ER), of a contractor and his competitors, on their success ratio and achieved profit. The key results of this investigation were checked analytically using order statistics by McCaffer, [24], who summed them up in six typical and indicative situations. McCaffer's results served as a good check on the accuracy of the preliminary simulation experiments carried out by the authoress in view of finding the number of simulations required to give a satisfactory degree of agreement with these results.

It was noted that the limits of the distribution of bids, and hence the integration limits, differ between McCaffer's solution and the simulation program developed in this thesis. Therefore, to be able to draw conclusions about the accuracy of the program, the six situations considered by McCaffer were solved analytically applying the limits used in the program and their results were the ones against which the computer program was checked.

In this thesis mark-up is expressed in terms of prime cost whereas in McCaffer's papers mark-up is in terms of the tender price or bid.

To illustrate the difference between the two sets of limits, situation one is solved using these two sets. All the relations for the probability of success and the expected values, used in this section were derived by McCaffer.

Given a uniform distribution in the range (a,b), Fig. (5.1), so that for any bid x, where $a \leqslant x \leqslant b$, and, if five bids are selected and the lowest is in the range (L - dL) to (L), then all the others must be in the range (L) to (b).

The probability of one being in the range (L - dL) to (L) is:

$$\frac{dL}{b - a} \tag{5.1}$$

The probability of the other 4 being in the range (L) to (b) is:

$$\left[\frac{b - L}{b - a} \right]^4 \tag{5.2}$$

Therefore, the probability of one being in the range (L - dL) to (L) and the other four being in the range (L) to (b) is

$$\frac{dL}{(b-a)} \left[\frac{b-L}{b-a} \right]^4 \tag{5.3}$$

Since any one of the five bidders can be the lowest, then the probability density function of the lowest bid is given by:

$$f(L) = 5 \left[\frac{1}{(b-a)} \left[\frac{b-L}{b-a} \right]^4 \right] \tag{5.4}$$

and the expected value of this function is:

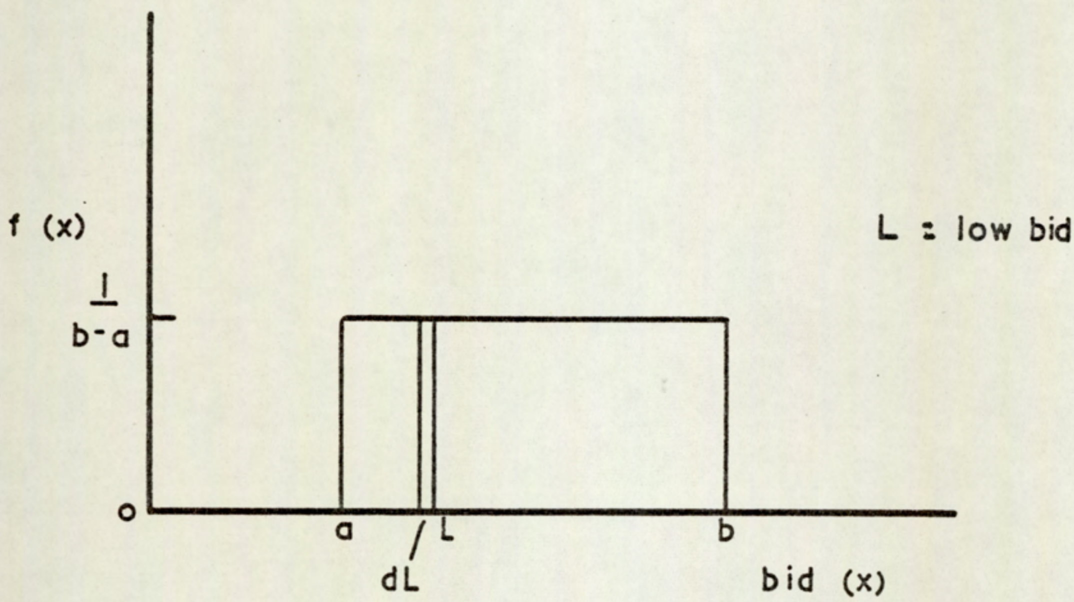


Fig .5.1

$$E(L) = \int_a^b 5 \frac{1}{(b-a)} \left[\frac{b-L}{b-a} \right]^4 L \, dL \qquad (5.5)$$

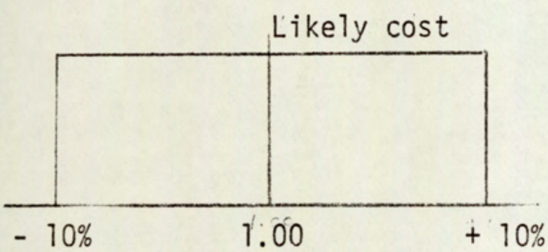
$$= a + \frac{(b-a)}{6} \qquad (5.6)$$

Following are the six situations considered by McCaffer:

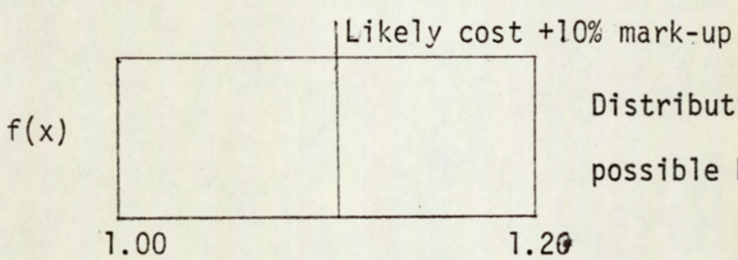
<u>Situation 1</u>:

In this situation, contractor E and his four competitors have an estimation accuracy of ±10% and a mark-up of 10%.

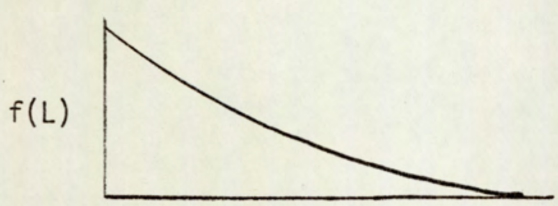
a) McCaffer's limits:



Distribution of cost estimates



Distribution of possible bids



Distribution of winning bids

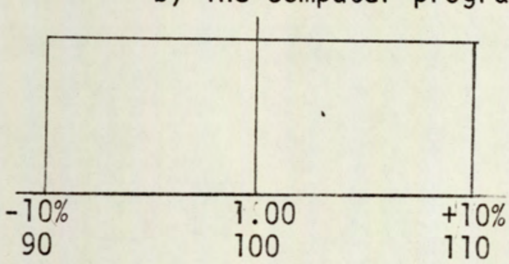
The expected value of the winning bid

$$E(L) = a + \frac{(b-a)}{6}$$

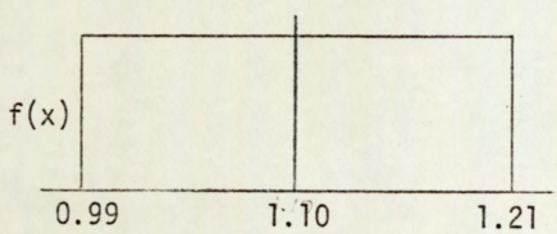
$$= 1.00 + \frac{(1.20 - 1.00)}{6} = 1.033$$

Since the likely cost is defined as 1.00, therefore actual achieved profit is 3.3%.

b) The computer program limits:



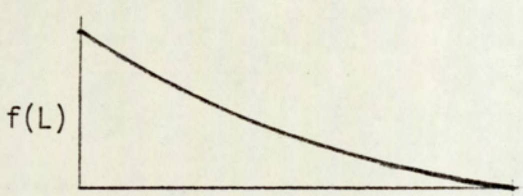
Distribution of cost estimate



Distribution of possible bids = Cost est. + 10% of cost est. =

$90 + 0.1(90) = 99$

$110 + 0.1(110) = 121$



Distribution of winning bid

Therefore, $E(L) = .99 + \frac{1.21 - .99}{6} = 1.0267$

i.e. achieved profit = 2.67%

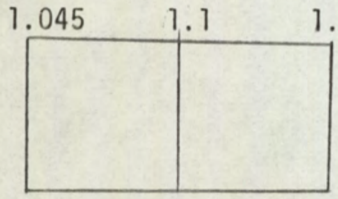
The success ratio for both cases is 0.2 as all contractors stand equal chances.

<u>Situation 2</u>:

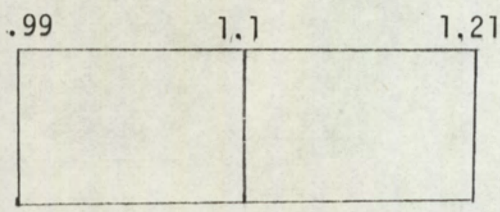
In this situation: E's estimation accuracy = ±5%

Competitors estimation accuracy = ± 10%

All have a mark-up of 10%



E's bid from this distribution



Competitors bids from this distribution

E's probability of winning is:

$$\int_{1.045}^{1.155} \left[\frac{(1.21 - L)^4}{0.11(0.22)^4} \right] dL = 0.0992$$

and

$$E(E) = \frac{\displaystyle\int_{1.045}^{1.155} \frac{1}{0.11} \cdot \frac{(1.21 - L)^4}{(0.22)^4} L \, dL}{.0992} = 1.07179$$

i.e. the achieved profit is 7.179%

Situation 3:

In this situation: E's estimation accuracy = ±5%.

E's mark-up = 7.5% to secure a share equal to situation 1 (i.e. 20%).

Competitors estimation accuracy = ±10%

Competitors mark-up = 10%

E's bid is in a range k to (k + 0.11) such that the probability of winning is 0.2 as in situation 1.

$$\int_{k}^{k+0.11} \frac{1}{0.11} \left[\frac{1.21 - L}{0.22} \right]^4 dL = 0.2$$

which results in

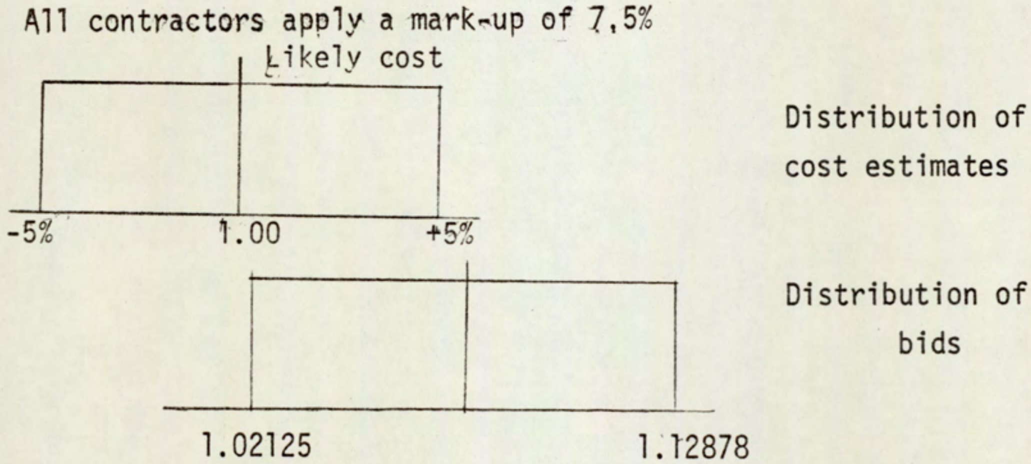
$$k = 1.029$$

Similar to situation 2, E's achieved profit is = 5.06%

Situation 4:

In this situation: All contractors have an estimation accuracy of ± 5%

All contractors apply a mark-up of 7.5%



Success ratio = 0.2 as all have the same chances

$$E\ (\text{winning bid}) = a + \frac{b-a}{6}$$

$$= 1.02125 + \frac{(1.12875 - 1.02125)}{6}$$

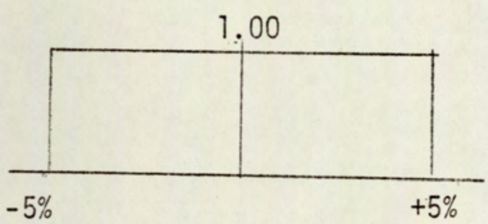
$$= 1.039166$$

i.e. the achieved profit is 3.9166%

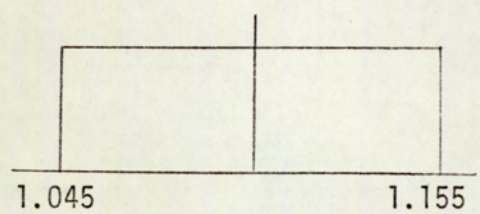
Situation 5:

In this situation: All contractors have an estimation accuracy of ±5%

All contractors apply a mark-up of 10%



Distribution of cost estimates



Distribution of bids

The success ratio is 0.2 as all contractors have equal chances.

The expected value of the winning bid is:

$$= a + \frac{b-a}{6}$$

$$= 1.045 + \frac{1.155 - 1.045}{6} = 1.06333$$

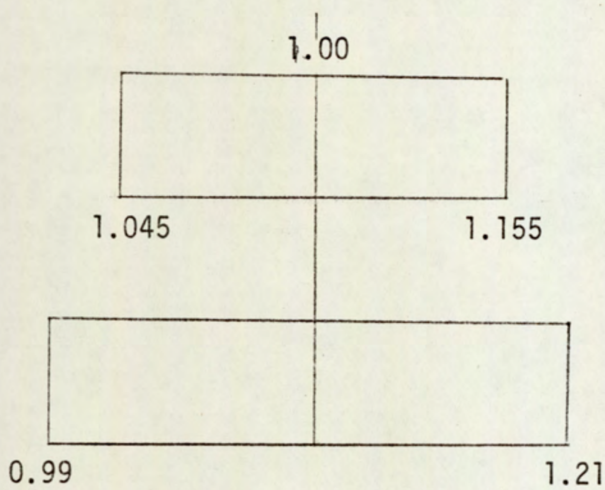
i.e. the achieved profit is 6.333%

Situation 6:

In this situation: Four contractors including E have an estimation accuracy = ±5%

The fifth has an estimation accuracy = ±10%

All five apply a mark-up = 10%



Distribution of 4 contractors bids including E.

Distribution of the 5th competitor's bid

The probability that the four competitors bids including E is greater than a value L is:

$$\int_{1.045}^{1.155} \frac{1}{0.22} \left[\frac{1.155-L}{0.11} \right]^4 dL$$

$$= .103$$

If the fifth competitor's bid is between 0.99 and 1.045 he must win, this probability is:

$$\frac{1.045 - 0.99}{1.21 - 0.99} = \frac{1}{4}$$

Therefore, the probability of the fifth contractor winning is:

$$0.25 + 0.103 = 0.353$$

The probability of any other contractor (including E) winning is:

$$\frac{1}{4}(1 - 0.353) = 0.16175$$

The expected value of E's bid is the same as situation 5, i.e. 1.0634.

The probability of the fifth contractor being in the range 1.045 to 1.155 is:

$$\frac{1.155 - 1.045}{1.21 - 1.045} = .666 = 2/3$$

$$a + \frac{b-a}{5} = 1.045 + \frac{(1.155 - 1.045)}{5} = 1.067$$

The probability of the fifth contractor being in the range 1.155 to 1.21 is:

$$\frac{1.21 - 1.155}{1.21 - 1.045} = .333 = 1/3$$

the expected value of E's winning bid is:

$$\frac{2}{3} \times 1.0634 + \frac{1}{3} \times 1.067 = 1.0645$$

i.e. the achieved profit = 6.45%

A computer program, whose flow chart is presented in Appendix (7.2), was developed to conduct the simulation study using the PRN's generated by subroutine RANDY which is presented in Appendix (7.1). The number of simulations required to yield results comparable to the analytic solutions was found to be (500). The computer program results are compared with the analytic ones evaluated in this section and are presented in Table (5.1). It can be seen that very good agreement is obtained between the simulation and analytic results for a fairly low number of simulations which gives confidence in the PRN generation subroutine and the simulation technique adopted.

5.2 Application of the concept of maximizing the expected profit

A computerised simulation investigation was conducted to study the influence of the level and type of estimation accuracy and the mark-up policy on the results obtained by using this concept. The following assumptions, which were guided by the values used in the published literature or the recommendations of contracting firms consulted during the course of this research were made:

a) The number of computing contractors is equal to five.

b) The levels of estimation accuracy considered (ER) were ±5%, ±10% and ±15%.

c) The true contract cost was fixed at a hypothetical figure of 100.

d) The mark-up, M, for the four competitors was fixed at 10% of the estimated cost while, for the fifth contractor, E, the mark-up M(E) varies from 5% to 15%.

e) The distribution of the estimation accuracy was assumed to be uniform by, [8], and normal by, [29]. Therefore for the purpose of this investigation, sampling from both the uniform distribution and the normal distribution were considered, for estimating accuracies (ER) of ±5%, ±10% and ±15%. * In addition, two types of curtailed normal distributions were considered, where 2σ= ER and 3σ= ER.

* Note that in the computerised sampling from the two normal distributions, generated values of x outside the range x = C±ER are assumed to be equal to the appropriate extreme values.

TABLE (5.1)

Situation	Analytical solution		Computerised simulation	
	Success ratio %	Average net profit %	Success ratio %	Average net profit %
1	20.0	2.67	19.66	2.686
2	9.92	7.179	9.76	7.223
3	20.0	5.06	19.140	5.091
4	20.0	3.9166	19.66	3.926
5	20.0	6.333	19.66	6.343
6	16.175	6.45	15.82	6.474

If ER is an informed but subjective estimate of the likely estimating accuracy, then for a particular value of ER where ±ER defines the range of the distribution, the three distributions of the prime cost (c) are shown in fig. (5.2).

In certain cases it was found that no maximum value for the expected profit was found in the mark-up range 5% to 15%, therefore, further cases were considered in the range 0% to 5% or 15% to 20% depending on where the maximum value is expected.

For the uniform distribution of estimation accuracy, the computer program developed for section (5.1) was used. For sampling from the two types of normal distributions two new programs were developed and their flow charts are presented in Appendix (7.2).

The results obtained from this study are shown in Figs.(5.3) to (5.15). It can be seen from these figures, that, regardless of the type of distribution of the estimation accuracy, a general trend exists between both the success ratio versus the mark-up of the fifth competitor, and the average net profit versus the same mark-up for each accuracy.

The relationships between the success ratio and the mark-up, whose determination is the central aim of all bidding models, are plotted for the various levels and types of estimation accuracy in Figs. (5.3) to (5.5). For all types of estimation accuracy, the three levels meet at the point of 10% mark-up and 20% success ratio. This is because the competitor's mark-up is 10% and, when the mark-up of the fifth contractor M(E) is also 10%, all bidders stand the same chance of winning. As their number is five, this ratio is 20%. When M(E) > 10% the shapes of the curves are similar for the three types of estimation accuracy, with the higher success ratio associated with the low accuracy (±15%). This is because the competitors are applying a mark-up of 10% and contractor E, who is applying a mark-up greater than 10%, can only beat them when their estimation accuracy is bad. When M(E) < 10% the relationship is linear for all types of estimation accuracy at ±10% and ±15%. However for ER = ±5% the success ratio remains very high when the M(E) is low and drops rapidly to a value of 20% just before M(E) = 10%. This is because the accuracy is high and as the fifth contractor is applying a mark-up less than his competitors he stands a better chance of being the winner. This is more so when the estimation accuracy is normally distributed as it most likely results in a small distribution of bids than that of a uniform distribution as will be explained in the profit case.

From Figs. (5.6) to (5.8) it can be concluded that a higher average net profit is associated with better estimation accuracy. For M(E) = 10%, and when the estimation accuracy was improved from ±15% to ±5%, the average net profit improved from -0.97% to 6.34% for the uniformly distributed case, from 0.29% to 6.76% for the normally distributed case (2σ = ±ER%), and from 3.53% to 7.85% for the normally distributed case (3σ = ±ER%).

In the normally distributed case ($3\sigma = \pm ER\%$) the average net profit increased by 38% when the estimation accuracy was improved from ±10% to ±5%. This result will be used later when comparing with a variable job value problem. These results also indicate that more profit is achieved at the low mark-up side if the distribution of the estimation accuracy is assumed to be normal. This is due to the fact that when the estimation accuracy is normally distributed, the bids fall most likely in a small range around the true likely cost and the probability of having an estimate at the lower end of the estimation accuracy range is small, particularly in the case where $3\sigma = ER$. This also explains why the slope of the curve of the normally distributed estimation accuracy is large at the low mark-up side but reduces as the mark-up is increased, because the small errors involved are only significant when the mark-up is low.

It can be seen from figs. (5.9) to (5.11) that the effect of the estimation accuracy on the expected profit depends on the mark-up. Higher expected profits are associated with better estimation accuracies at mark-ups under 10% only. If $M(E) > 10\%$ higher expected profits are sometimes associated with the poorer estimation accuracies. Taking the normally distributed ($3\sigma = \pm ER\%$) case as an example, for $M(E) = 5\%$ the expected profit increased by 124% when the estimation accuracy was improved from ±10% to ±5%. However if $M(E) = 15\%$ the expected profit is reduced by 95% for the same improvement in estimation accuracy. It can be concluded that if contractors are applying high mark-ups, they do not need to spend extra time, and hence cost, trying to improve their estimation accuracy.

However, because of the associated low probability of success with wide ranging estimating accuracies and high mark-ups the contractor must bid for more jobs (assuming that these are available) and, hence, the cost of estimating may still be high. In such cases job values are important.

There is a significant difference in the maximum expected profit for the three distributions of estimation accuracy when it is ±5%. This difference is reduced and the curves become more similar as the accuracy becomes ±10% and ±15% because the shape of the normal distribution approaches that of the uniform one.

To increase the scope of the investigation, the normally distributed estimation accuracy (2σ = ±ER%) was chosen to study the case where the four contractors, including the fifth (US), have an estimation accuracy of ±5% while that for the remaining one is ±10%. The mark-up for the four competitors, including the one with an estimation accuracy of ±10%, was fixed at 10%, while that of the fifth was varied between 5% and 15%. To illustrate the sensitivity of the result to the reduction of the estimation accuracy of the first contractor, the success ratio of the fifth contractor was 1 contract in 5 when all had an estimation accuracy of ±5% and a mark-up of 10%. This was reduced to 1 contract in 6, when the first contractor reduced his estimation accuracy to ±10%. The remaining results of the investigation are shown in Figs. (5.12), (5.13).

The uniform distribution of estimation accuracies of ±5%, ±10% and ±15% was chosen to study the sensitivity of the success ratio, average net profit, and expected value of the fifth contractor, to the change of mark-up of one of the four competitors. The results are shown in Table (5.2). and figs. (5.14), (5.15).

TABLE (5.2)

Bidder	M	ER	M	ER	M	ER	M	ER
A	10	5	7.5	5	5	5	10	5
B	10	5	10	5	10	5	5	5
C	10	5	10	5	10	5	10	5
D	10	5	10	5	10	5	10	5
E	10	5	10	5	10	5	10	5
Success ratio	1 in 5		1 in 7		1 in 12		1 in 12	
Average net profit	6.34		6.19		5.86		5.84	
E(profit)	1.24		0.863		0.504		0.483	

Bidder	M	ER	M	ER	M	ER	M	ER	M	ER
A	10	10	7.5	10	5	10	10	10	7.5	10
B	10	10	10	10	10	10	10	10	10	10
C	10	10	10	10	10	10	10	10	10	10
D	10	10	10	10	10	10	10	10	10	10
E	10	10	10	10	10	10	7.5	10	10	10
Success ratio	1 in 5		1 in 6		1 in 7		1 in 3		1 in 4	
Average net profit	2.686		2.527		2.352		1.13		0.928	
E(profit)	0.528		0.429		0.329		0.355		0.257	

Bidder	M	ER	M	ER	M	ER
A	10	15	7.5	15	5	15
B	10	15	10	15	10	15
C	10	15	10	15	10	15
D	10	15	10	15	10	15
E	10	15	10	15	10	15
Success ratio	1 in 5		1 in 6		1 in 6	
Average net profit	-0.97		-1.174		-1.303	
E (profit)	-0.191		-0.2092		-0.2095	

Uniform Dist.

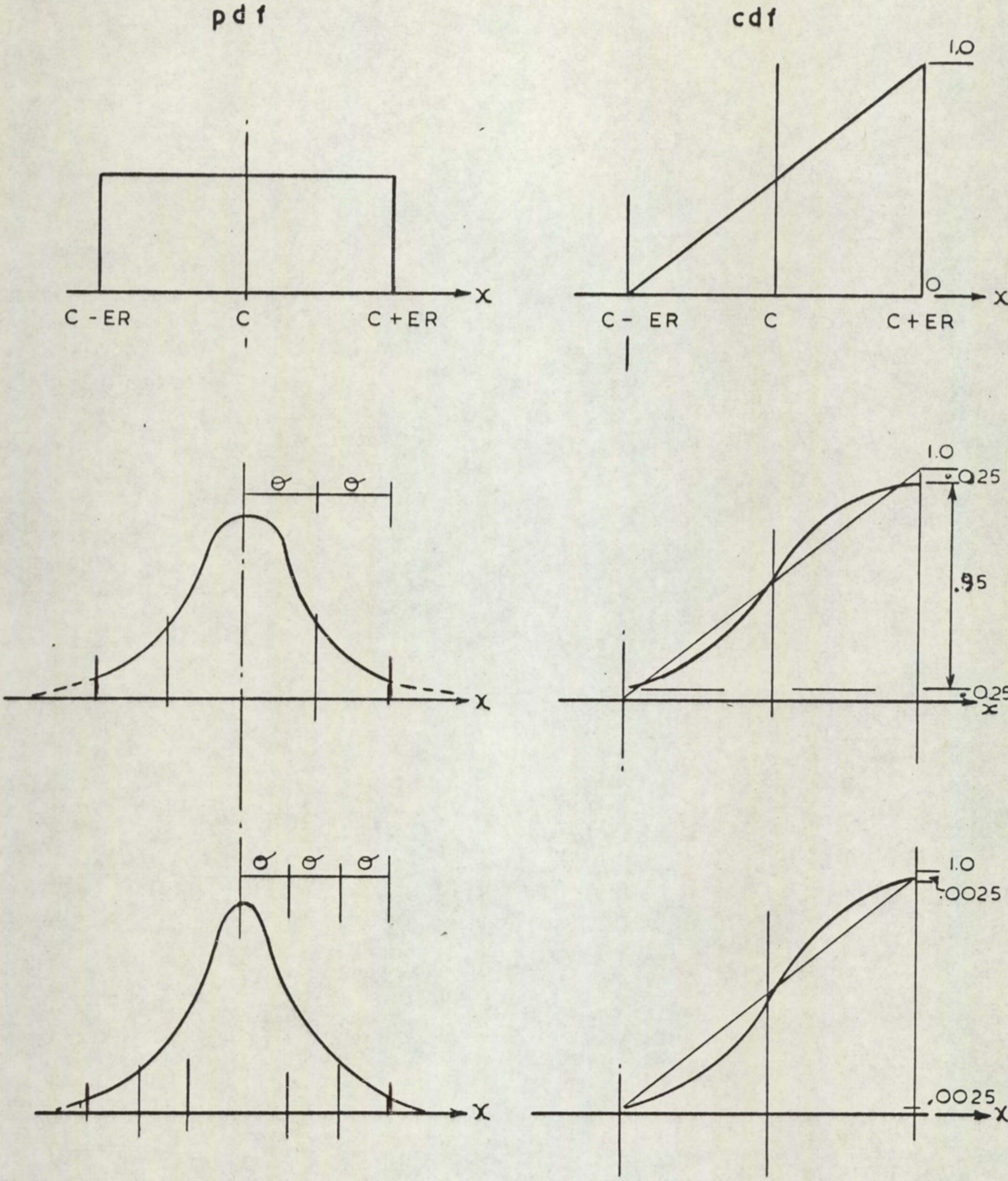


Fig .5.2

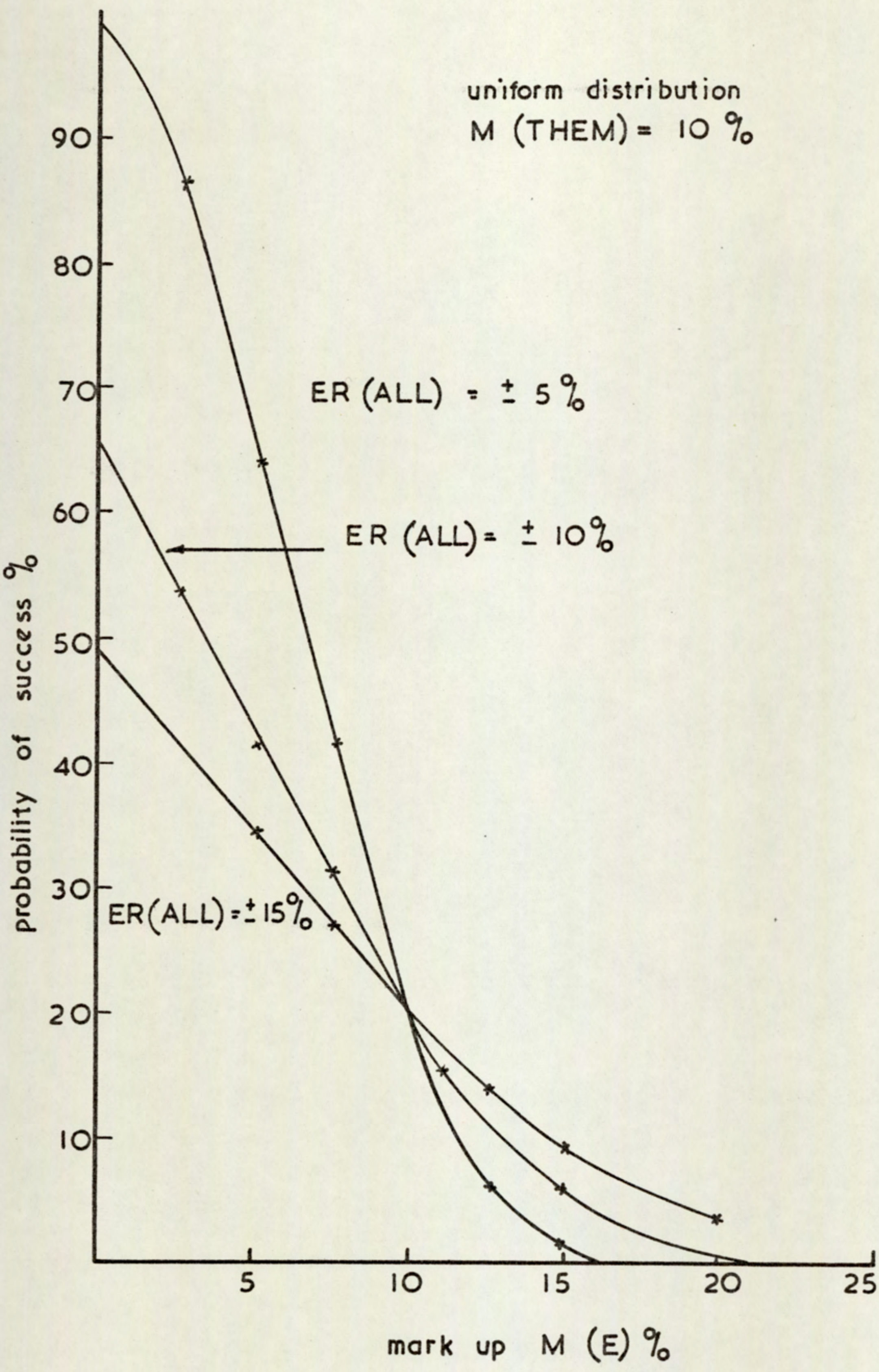

uniform distribution
M (THEM) = 10 %
ER (ALL) = ± 5 %
ER (ALL) = ± 10 %
ER (ALL) = ± 15 %
probability of success %
mark up M (E) %
90
80
70
60
50
40
30
20
10
5
10
15
20
25

Fig . 5. 3

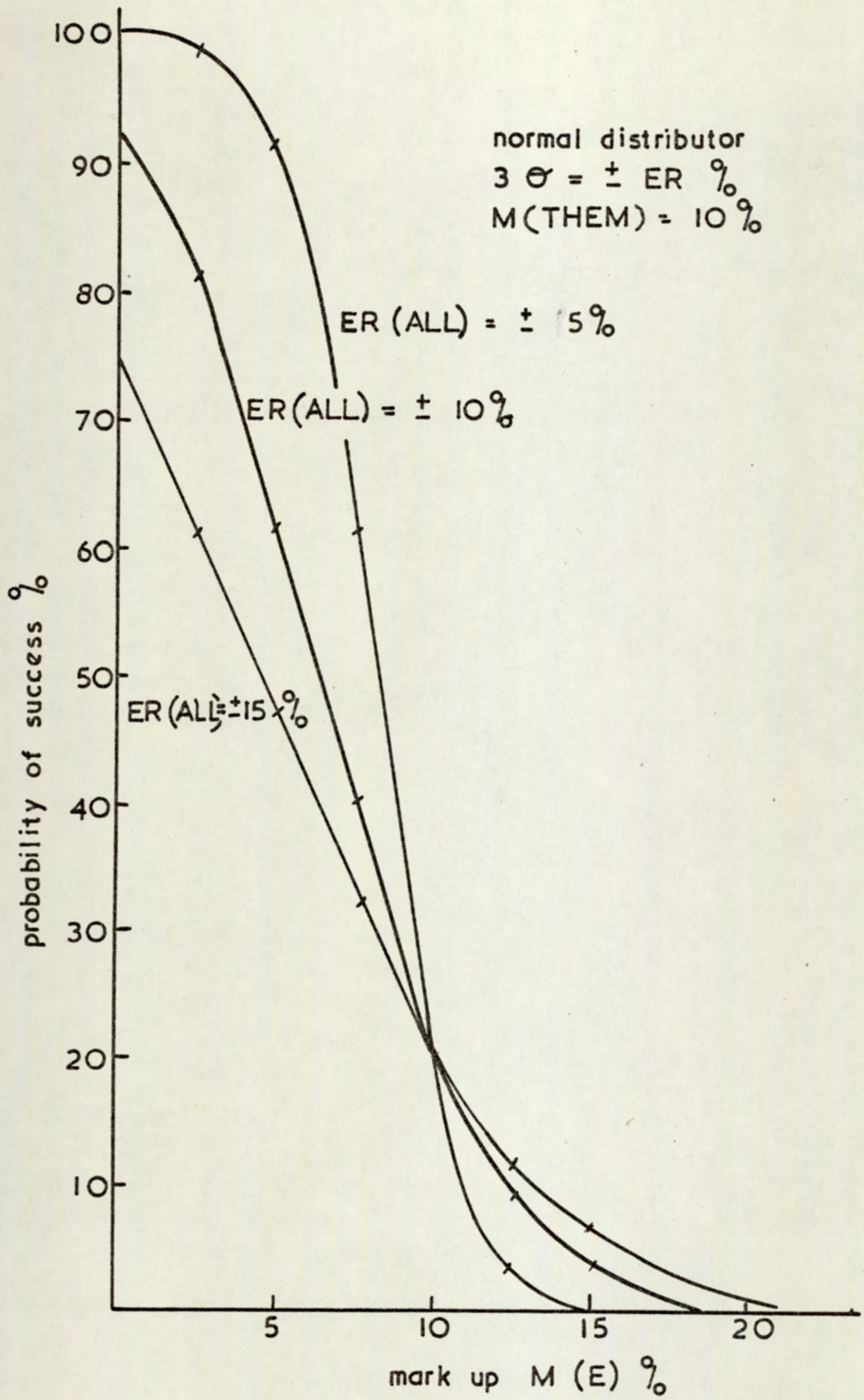

normal distributor
3 σ = ± ER %
M(THEM) = 10 %
ER (ALL) = ± 5%
ER(ALL) = ± 10%
ER (ALL)=±15%
probability of success %
100
90
80
70
60
50
40
30
20
10
5
10
15
20
mark up M (E) %

Fig. 5.4

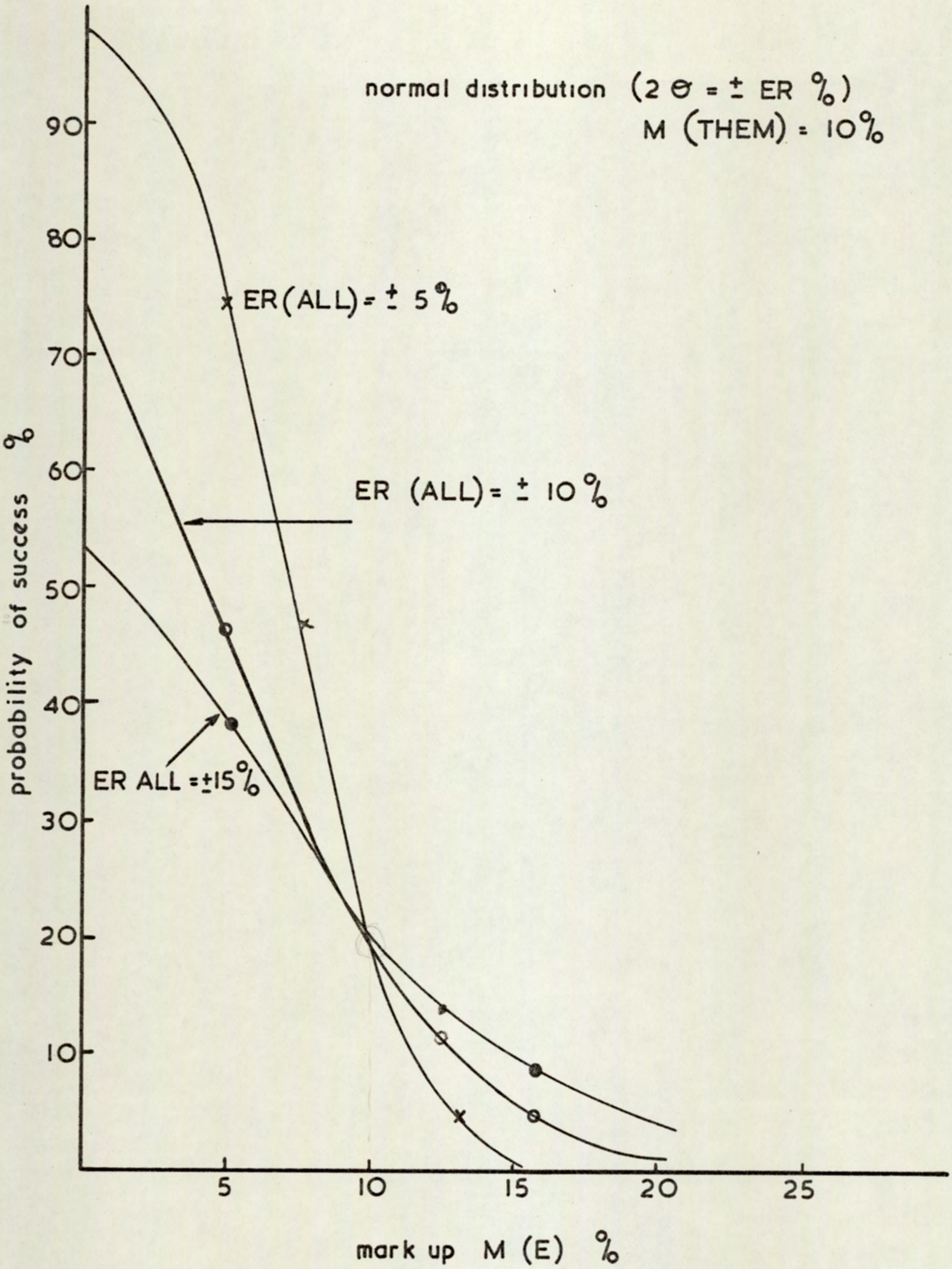

normal distribution ($2\sigma = \pm$ ER %)
M (THEM) = 10%
ER(ALL) = ± 5%
ER (ALL) = ± 10%
ER ALL = ±15%
probability of success %
mark up M (E) %
90
80
70
60
50
40
30
20
10
5
10
15
20
25

Fig. 5.5

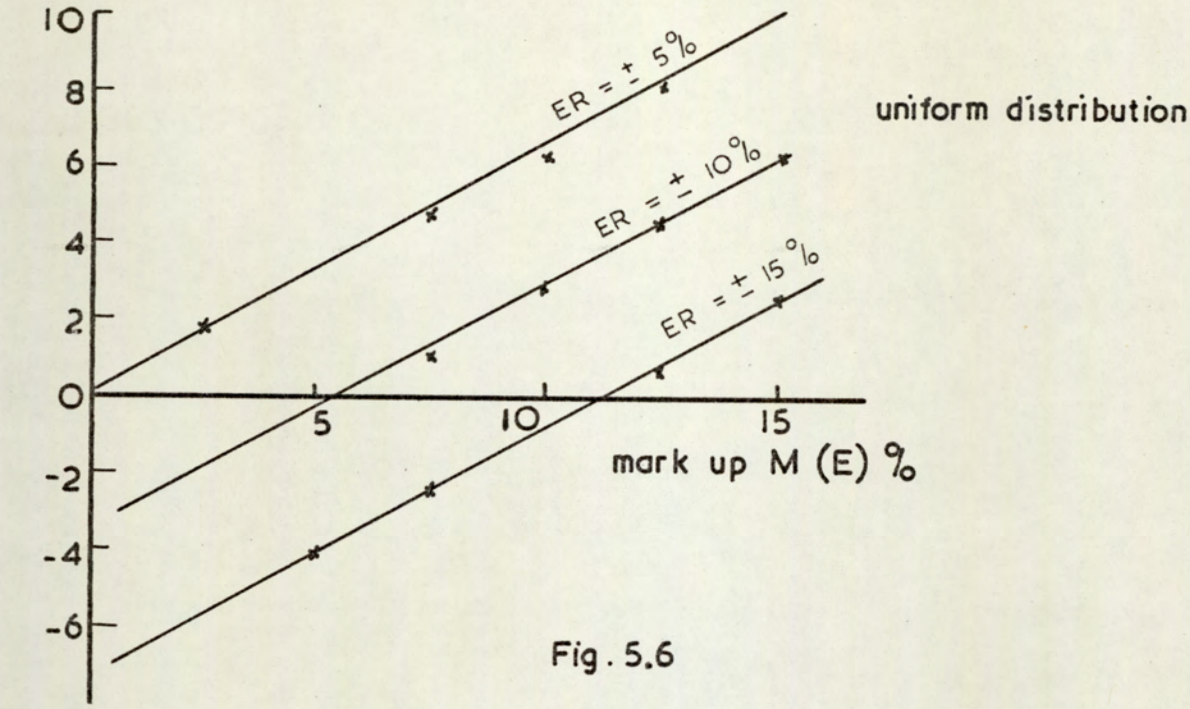


Fig. 5.6

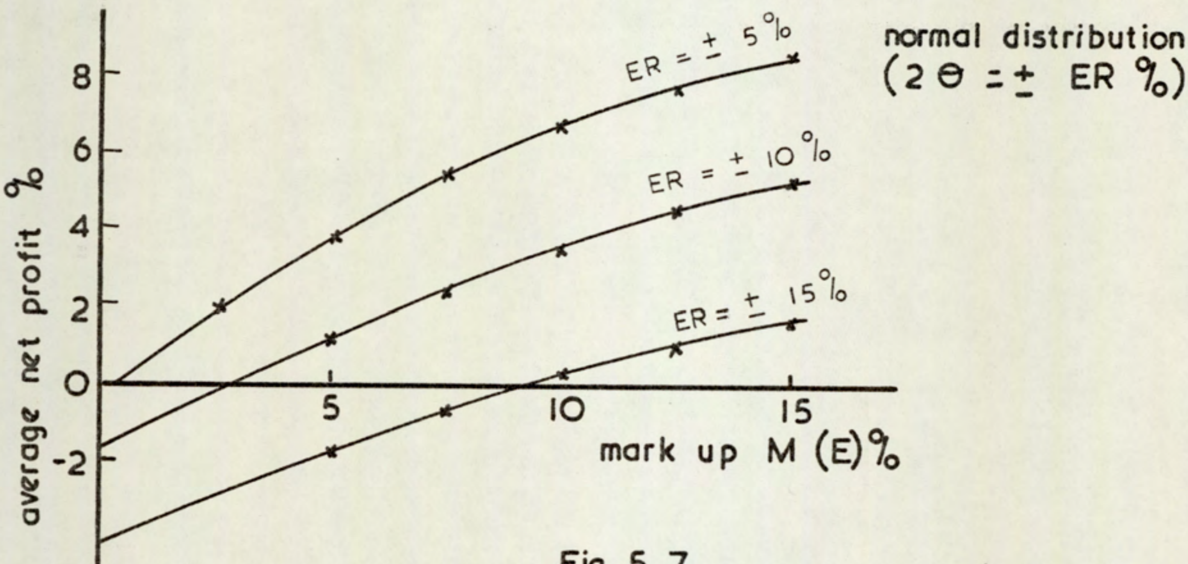


Fig. 5.7

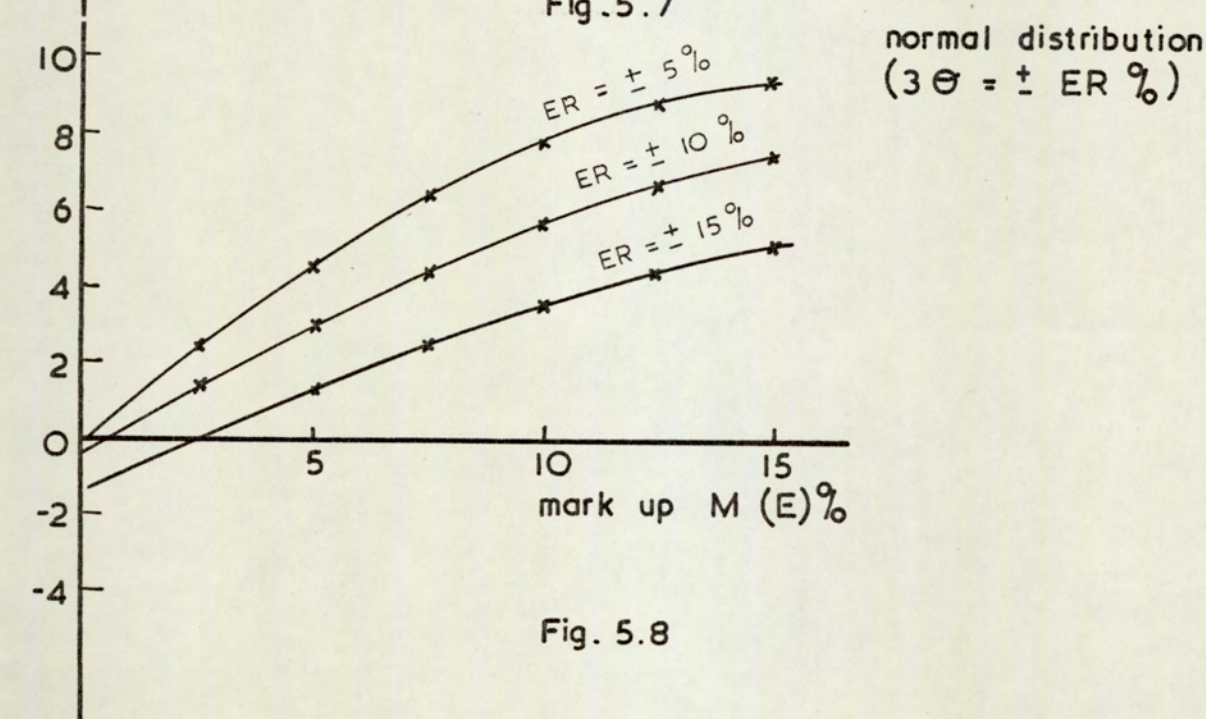


Fig. 5.8

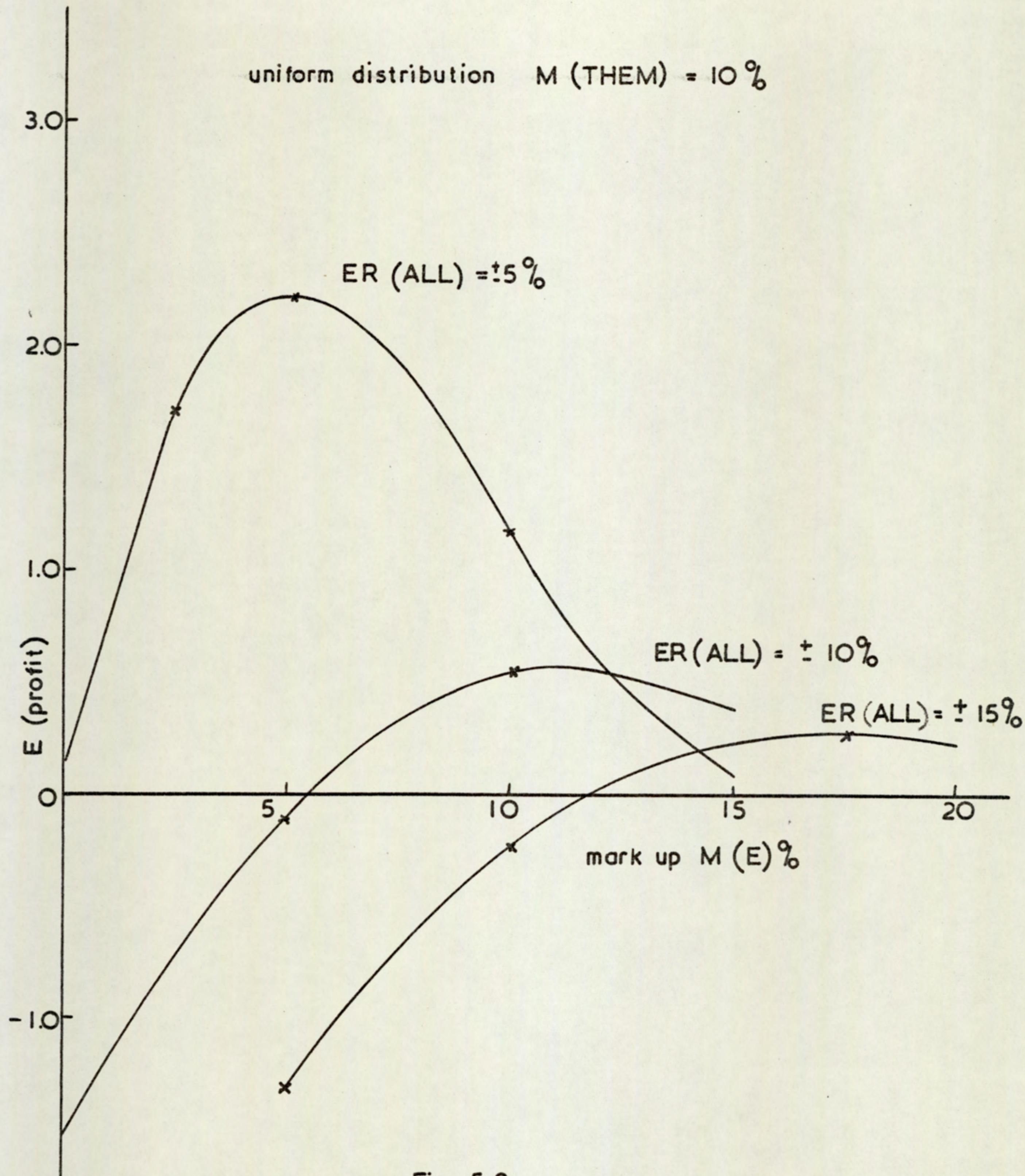
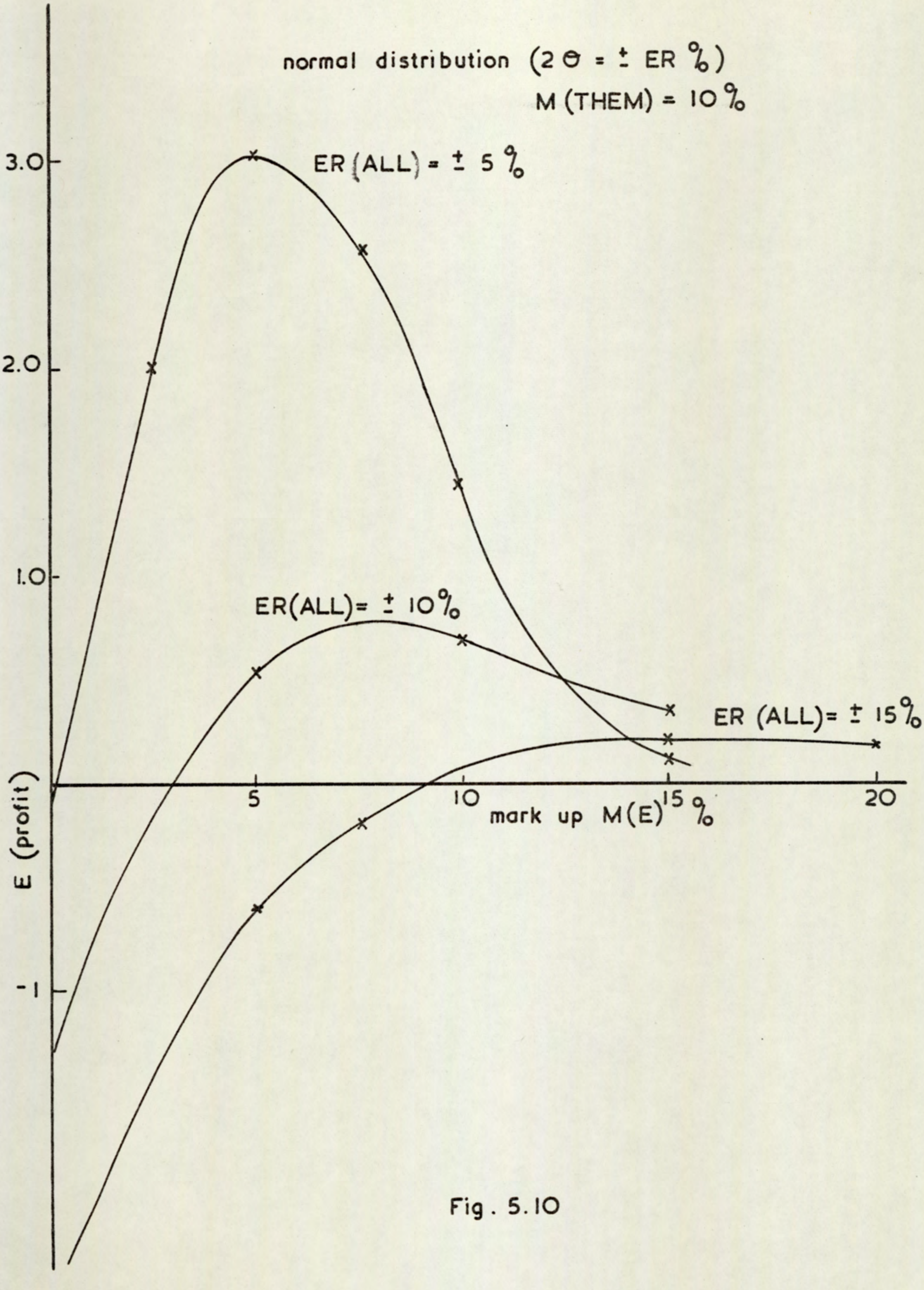

uniform distribution M (THEM) = 10 %
3.0
2.0
1.0
0
-1.0
E (profit)
ER (ALL) = ±5 %
ER (ALL) = ± 10%
ER (ALL) = ± 15%
5
10
15
20
mark up M (E) %

Fig. 5.9



normal distribution (2 Θ = ± ER %)
M (THEM) = 10 %
ER (ALL) = ± 5 %
ER(ALL) = ± 10%
ER (ALL) = ± 15%
3.0
2.0
1.0
-1
5
10
15
20
E (profit)
mark up M(E) %

Fig. 5.10

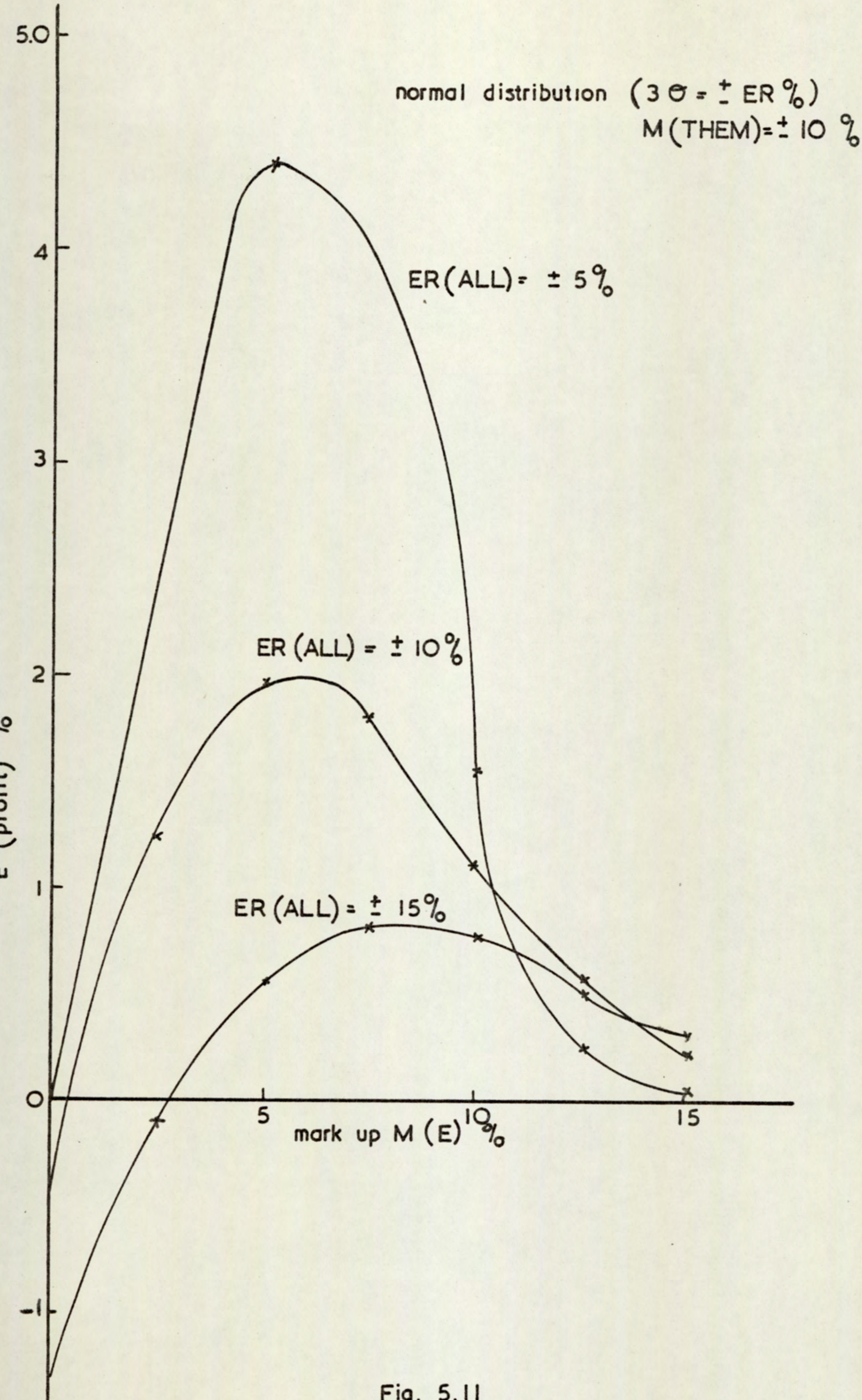

normal distribution (3σ = ± ER %)
M (THEM) = ± 10 %
ER (ALL) = ± 5%
ER (ALL) = ± 10%
ER (ALL) = ± 15%
E (profit) %
mark up M (E) %
5.0
4
3
2
1
0
-1
5
10
15

Fig. 5.11

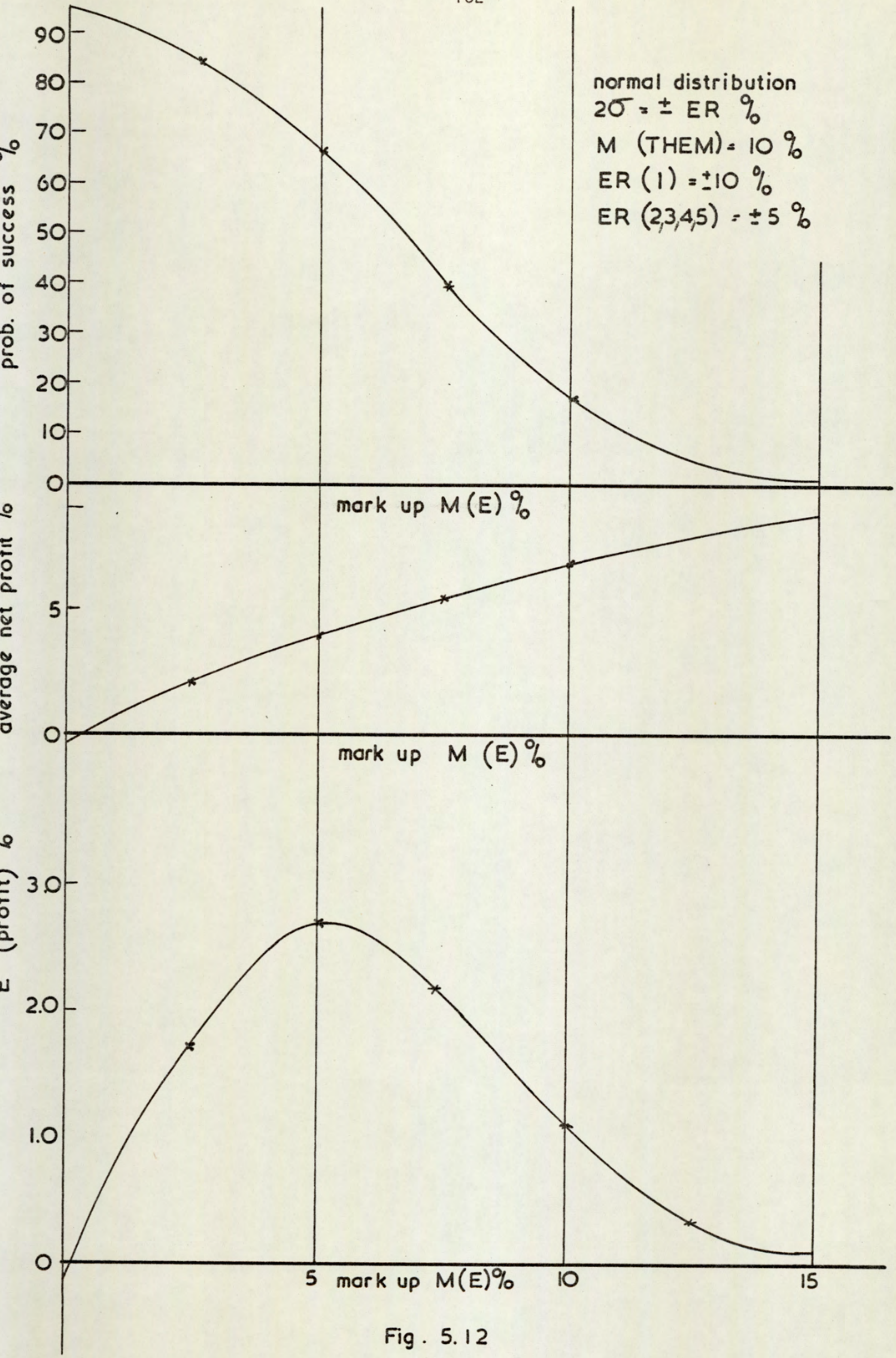

normal distribution
$2\sigma = \pm$ ER %
M (THEM) = 10 %
ER (1) = ±10 %
ER (2,3,4,5) = ± 5 %
prob. of success %
90
80
70
60
50
40
30
20
10
0
mark up M(E) %
average net profit %
5
0
mark up M (E) %
E (profit) %
3.0
2.0
1.0
0
5
mark up M(E)%
10
15

Fig. 5.12

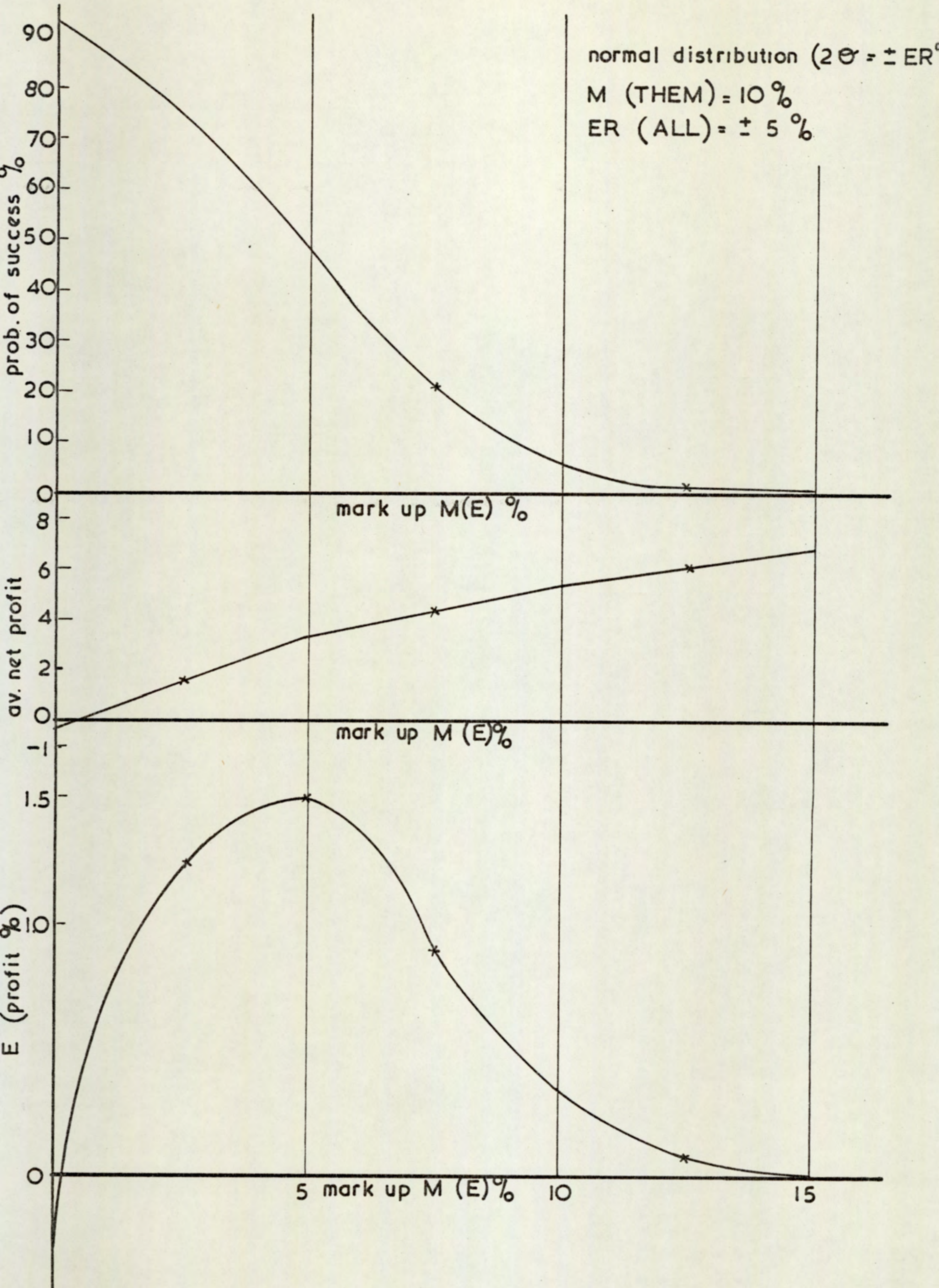

normal distribution (2σ = ± ER%)
M (THEM) = 10 %
ER (ALL) = ± 5 %
prob. of success %
90
80
70
60
50
40
30
20
10
0
mark up M(E) %
av. net profit
8
6
4
2
0
-1
mark up M (E)%
E (profit %)
1.5
10
0
5 mark up M (E)%
10
15

Fig . 5.13

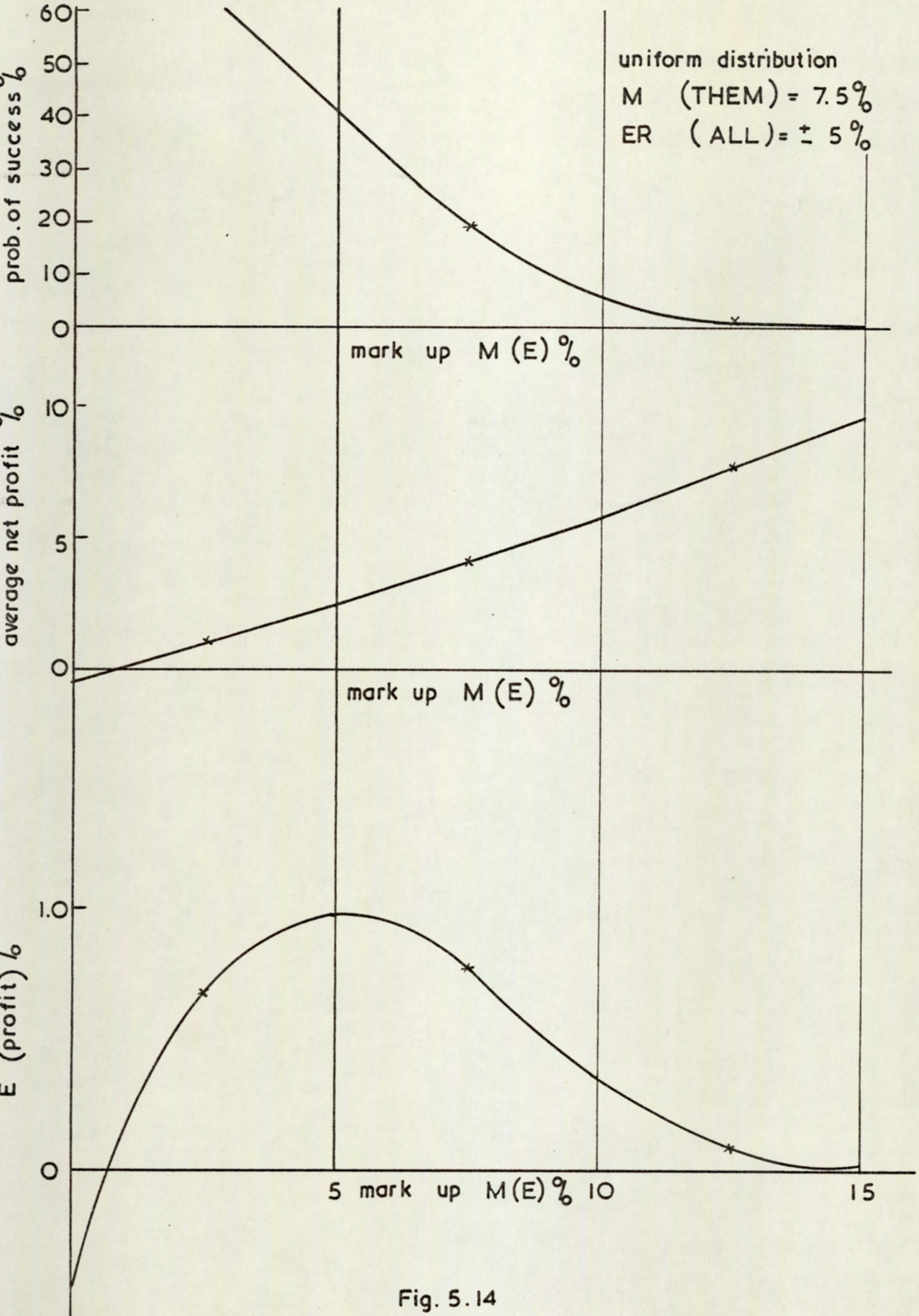

uniform distribution
M (THEM) = 7.5%
ER (ALL) = ± 5%
prob. of success %
60
50
40
30
20
10
0
mark up M (E) %
average net profit %
10
5
0
mark up M (E) %
E (profit) %
1.0
0
5 mark up M(E) % 10
15

Fig. 5.14

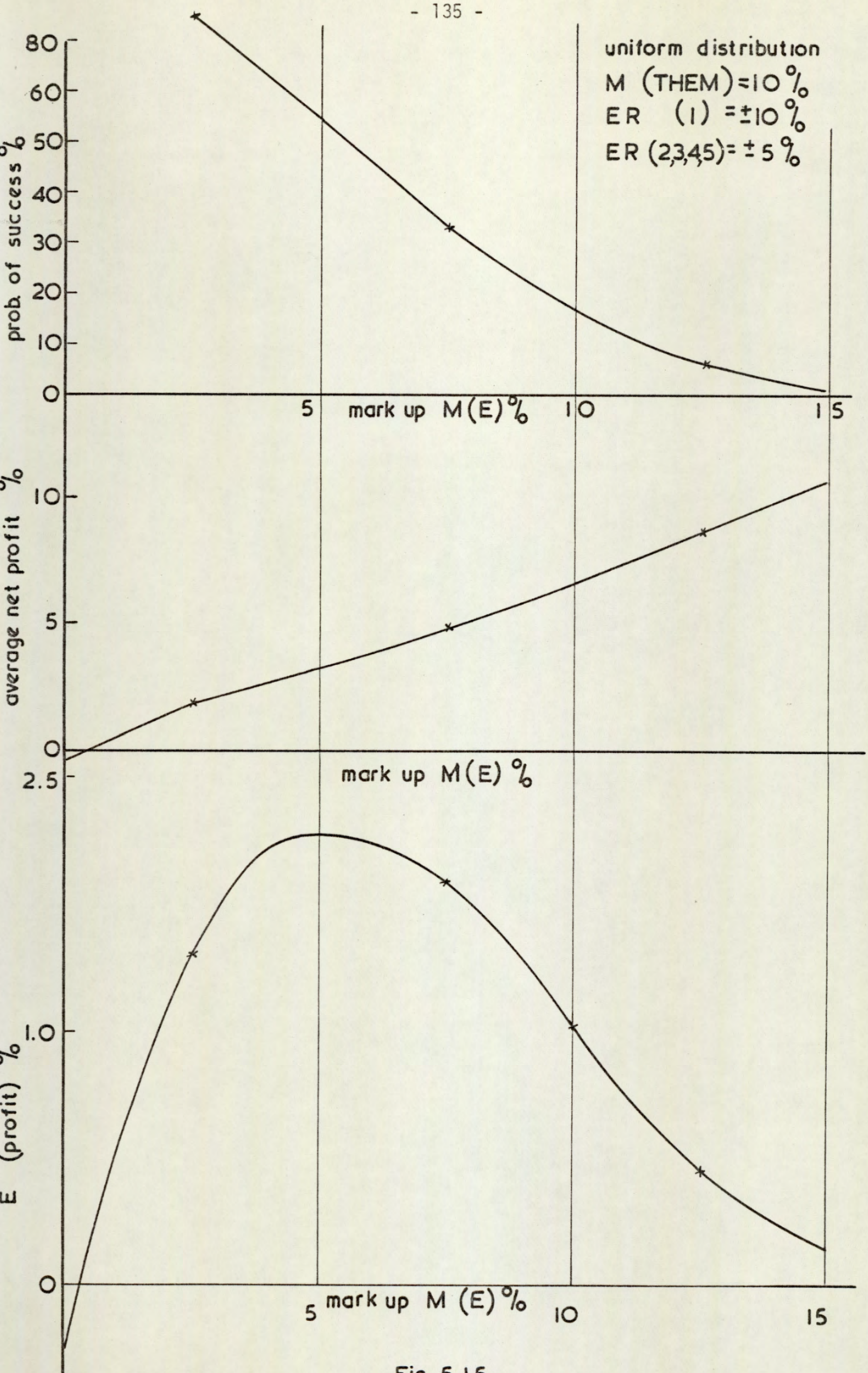

uniform distribution
M (THEM)=10 %
ER (1) =±10 %
ER (2,3,4,5)= ± 5 %
prob. of success %
80
60
50
40
30
20
10
0
5
mark up M(E)%
10
15
average net profit %
10
5
0
mark up M(E) %
E (profit) %
2.5
1.0
0
5
mark up M (E)%
10
15

Fig. 5.15

5.3 An investigation into the effect of the number of competitors:

In the previous section the number of contractors was fixed for all the bidding situations investigated. It was seen earlier that the number of competitors has an important effect on the results and an investigation was carried out to determine these effects. The uniform distribution of estimation accuracy was chosen with accuracies of ±5%, ±10% and ±15% for all the contractors. The mark-up of all the competitors was fixed at 10% and that of the last contractor M(E) was varied. The number of competitors was varied from 1 to 10.

Fig. (5.16) shows the effects on E's optimum mark-up and expected profit where it can be seen that this effect is considerable when the number of competitors is small but is insignificant for a large number of competitors. When the number of competitors was increased from 1 to 4, the optimum mark-up was reduced by 38%, while an increase from 4 competitors to 9 reduced the optimum mark-up by 10% only. The corresponding values for the expected profit are 52% and 34% respectively. This study was limited to the case ± 5% estimation accuracy only as it required varying M(E) in 0.5% and 0.25% steps in the optimum region to determine its value accurately. The same conclusion was arrived by Gates, [7].

The effect of the number of competitors on the optimum bid, which is the bid submitted at the optimum mark-up maximizing the expected value of the profit, for the three levels of estimation accuracy can be seen in Figs. (5.17) to (5.19). For the ±5% estimation accuracy the effect of increasing the number of competitors results in decreasing the optimum bid value and reduce the mark-up at which it occurs. For the cases of ±10% and ±15% estimation accuracy, although the optimum bid value decreases as the number of competitors is increased, the mark-up of the optimum bid remains constant to within (±0.5%). The other observation made in the case of these two levels, is that increasing the mark-up beyond the optimum has less and less effect on the value of the expected profit as the number of competitors is increased and the level of estimation accuracy is reduced. This is implied by the slope of the curves which gets flatter (approaches zero) beyond the point of optimum mark-up as the number of competitors is increased and is more so for the ±15% level of estimation accuracy.

The effect on the relationship between the mark-up M(E) and the probability of success of the three levels of estimation accuracy is shown in Figs. (5.20) to (5.22). It can be concluded that the number of competitors has little effect on the case of good estimation accuracy ER(±5%) as the curves shown in Fig. (5.20) are in a thin band. The effect increases as the accuracy becomes ±10% and ±15% as the width of this band increases in Figs. (5.21) and (5.22) respectively. At M(E) = 5%, the success ratio is reduced by 43% when the number of competitors is increased from 1 to 10 for an estimation accuracy of ±5%. This value becomes 58% and 80% for accuracies ±10% and ±15% respectively. In fig.(5.23) the effect of three selected mark-ups M(E) = 5%, 10%, and 15% for the three levels of estimation accuracy on the relation between the number of competitors and the probability of success is shown. In the case of M(E) = 10% all contractors apply the same mark-up, therefore the level of estimation accuracy has no effect on their success ratio which is governed by their number only. This curve follows Gates' model as it gives all contractors equal chances which add up to unity.

It is also seen that when a contractor applies a lower mark-up than his competitors M(E) = 5%, improving the level of estimation accuracy gives him a higher success ratio. However, if his mark-up is more than that of his competitors M(E) = 15%, then improving the level of estimation accuracy will make his competitors more competitive and hence reduces his success ratio, therefore his success ratio is higher when the estimation accuracy is ±15%.

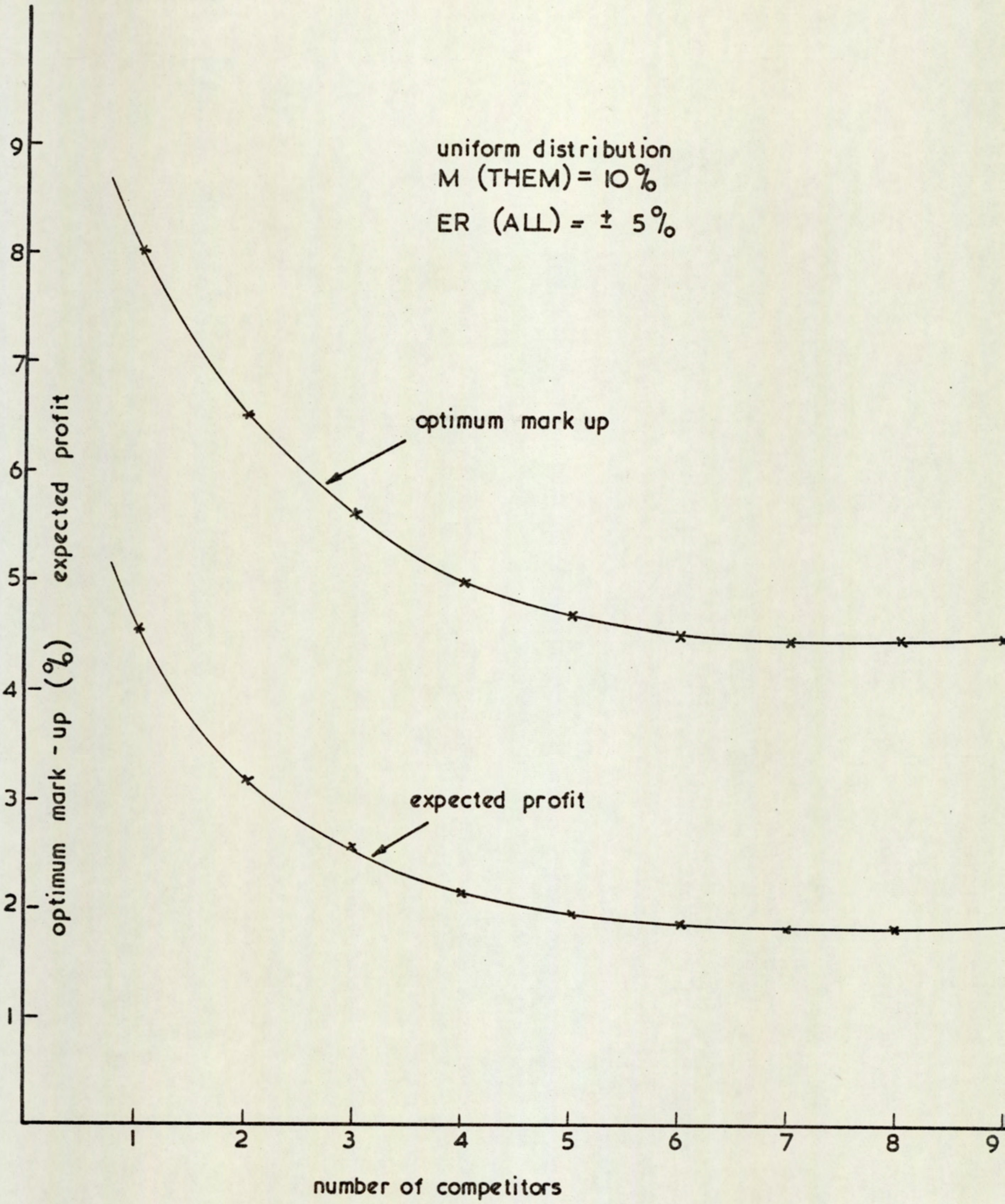

uniform distribution
M (THEM) = 10%
ER (ALL) = ± 5%
optimum mark up
expected profit
optimum mark - up (%) expected profit
number of competitors
1
2
3
4
5
6
7
8
9

Fig. 5.16

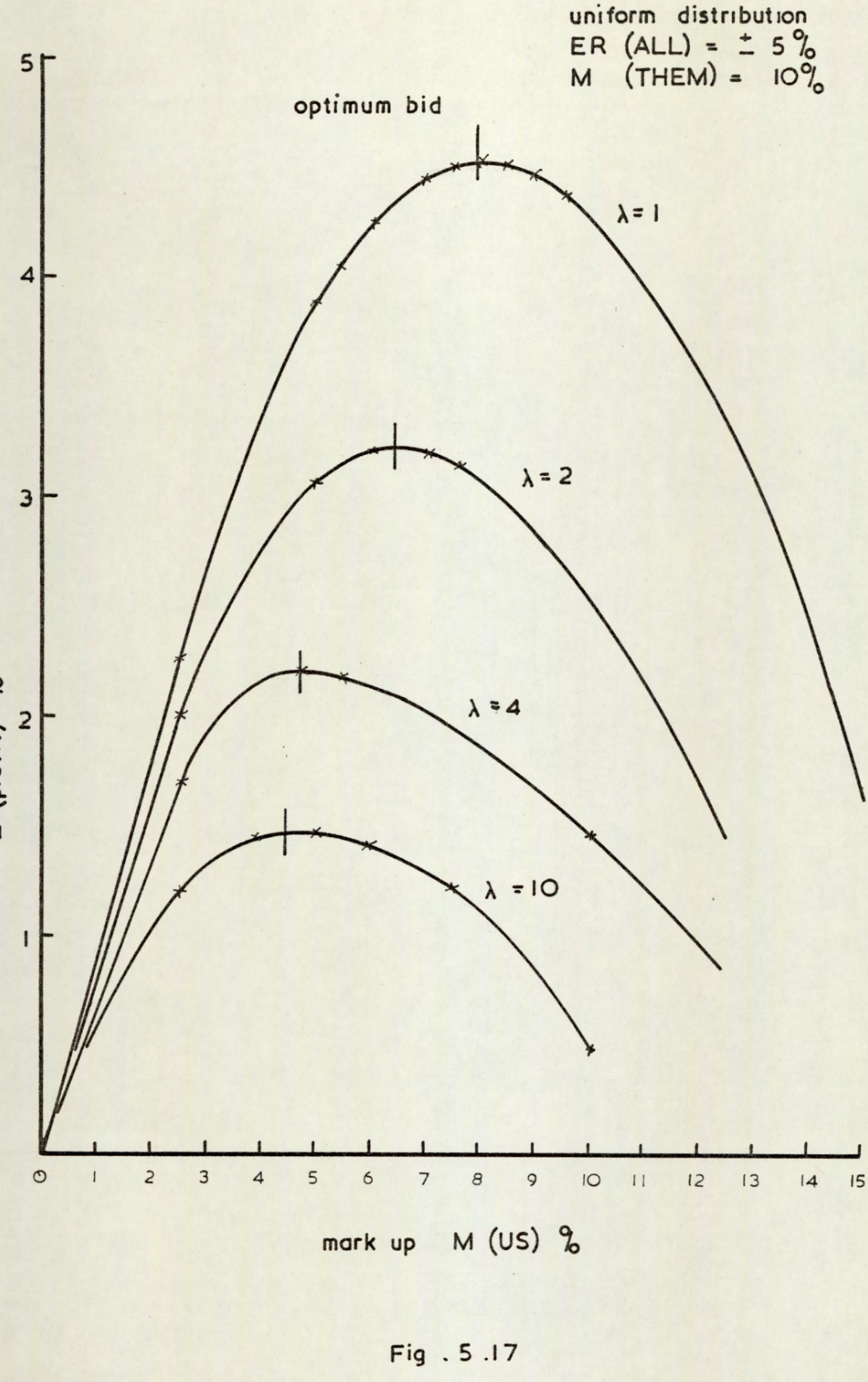

uniform distribution
ER (ALL) = ± 5 %
M (THEM) = 10%
optimum bid
λ = 1
λ = 2
λ = 4
λ = 10
E (profit) %
mark up M (US) %
0
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15

Fig . 5 .17

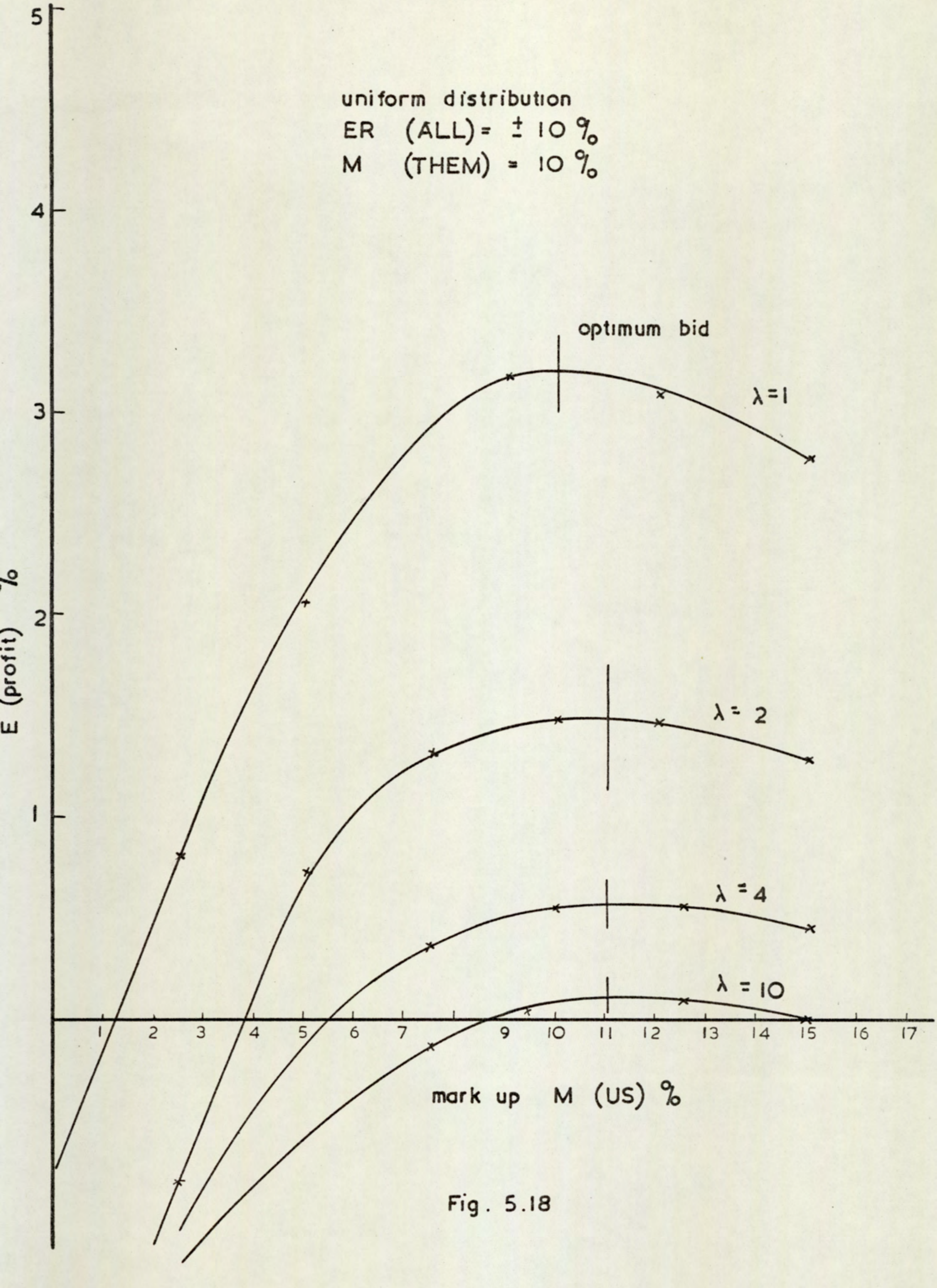

uniform distribution
ER (ALL) = ± 10 %
M (THEM) = 10 %
optimum bid
λ=1
λ= 2
λ =4
λ = 10
E (profit) %
mark up M (US) %
5
4
3
2
1
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17

Fig. 5.18

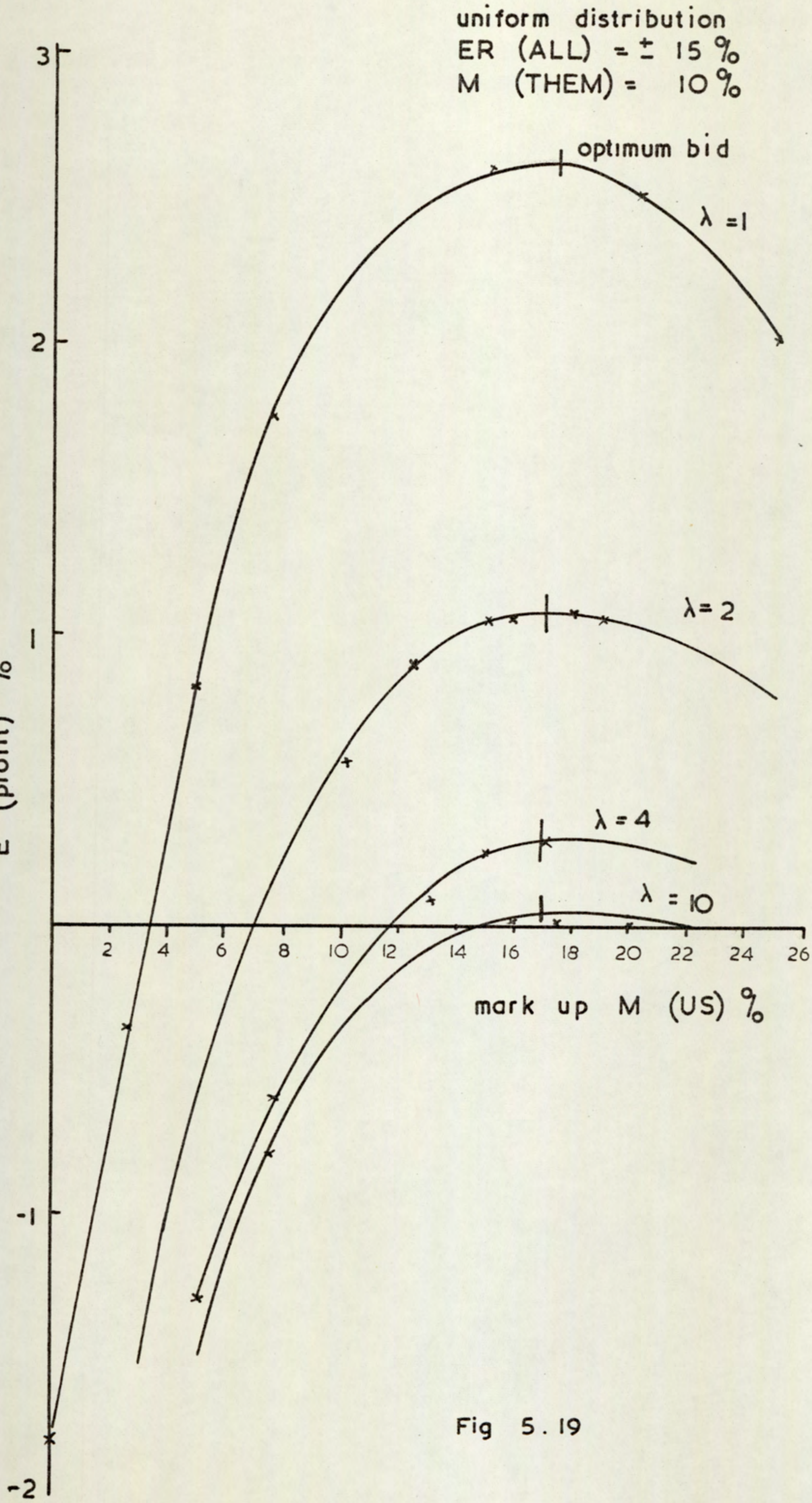

uniform distribution
ER (ALL) = ± 15 %
M (THEM) = 10 %
optimum bid
λ =1
λ= 2
λ = 4
λ = 10
E (profit) %
3
2
1
-1
-2
2
4
6
8
10
12
14
16
18
20
22
24
26
mark up M (US) %

Fig 5.19

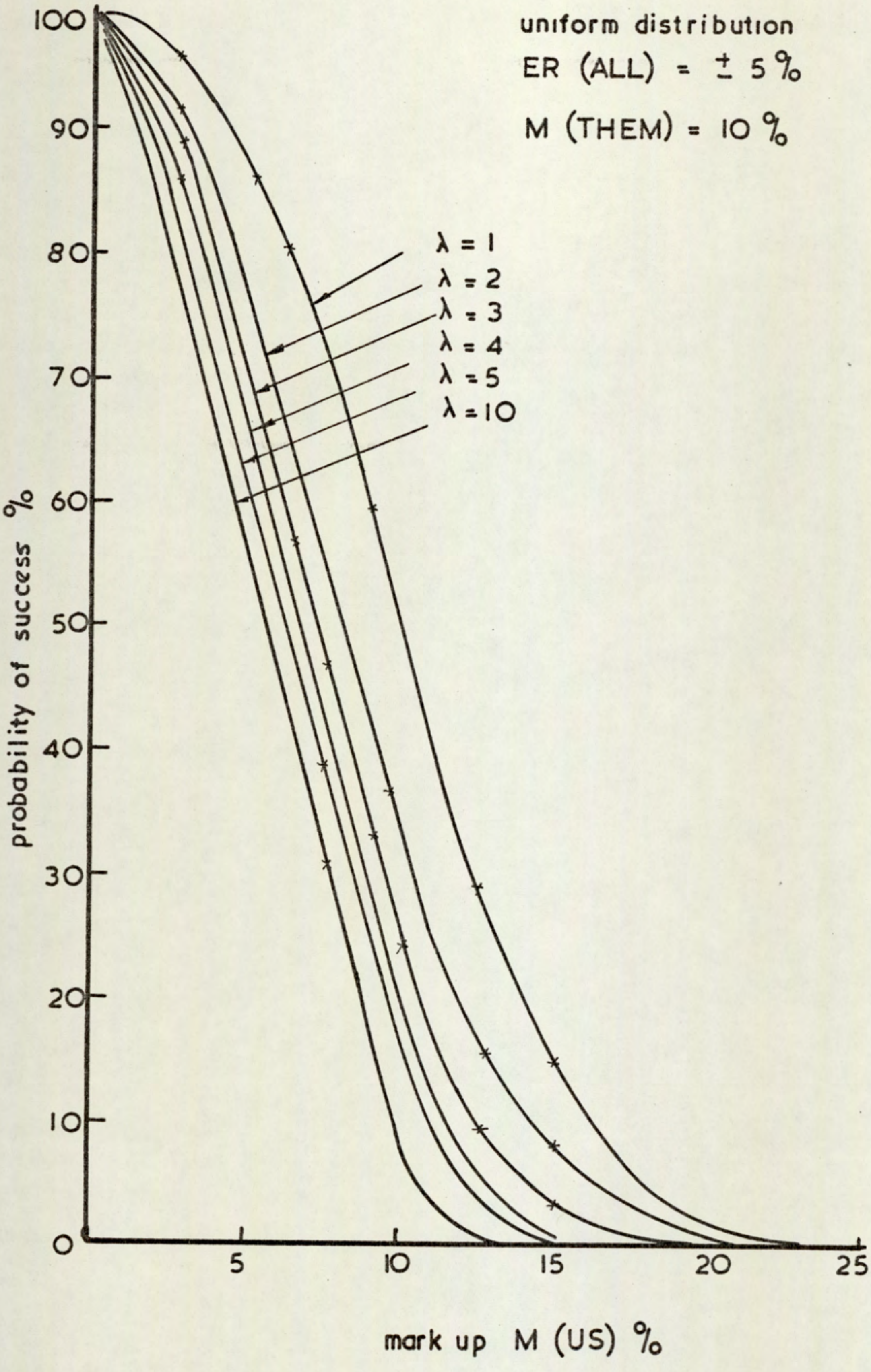

uniform distribution
ER (ALL) = ± 5 %
M (THEM) = 10 %
λ = 1
λ = 2
λ = 3
λ = 4
λ = 5
λ = 10
probability of success %
0
10
20
30
40
50
60
70
80
90
100
5
10
15
20
25
mark up M (US) %

Fig.5.20

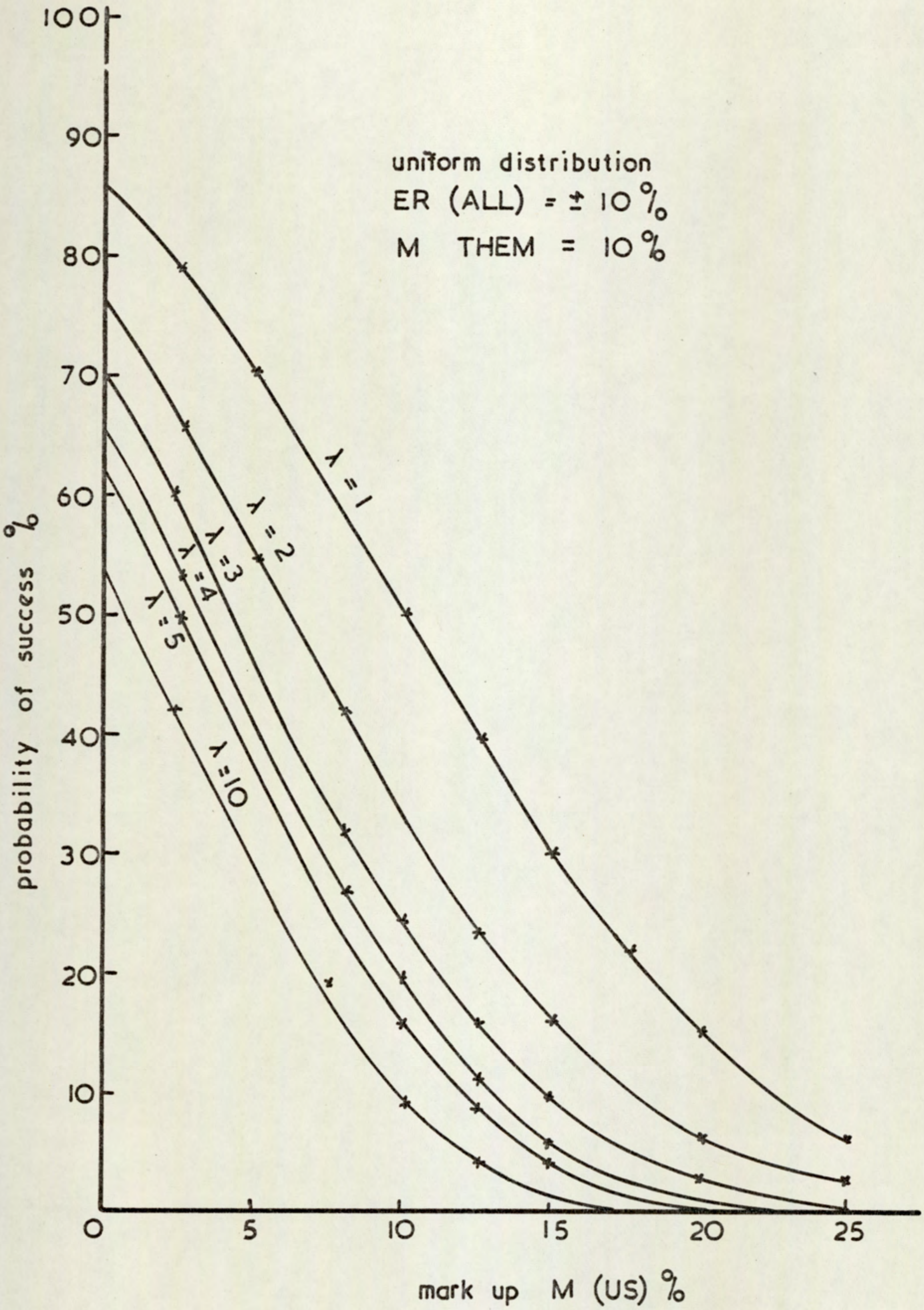
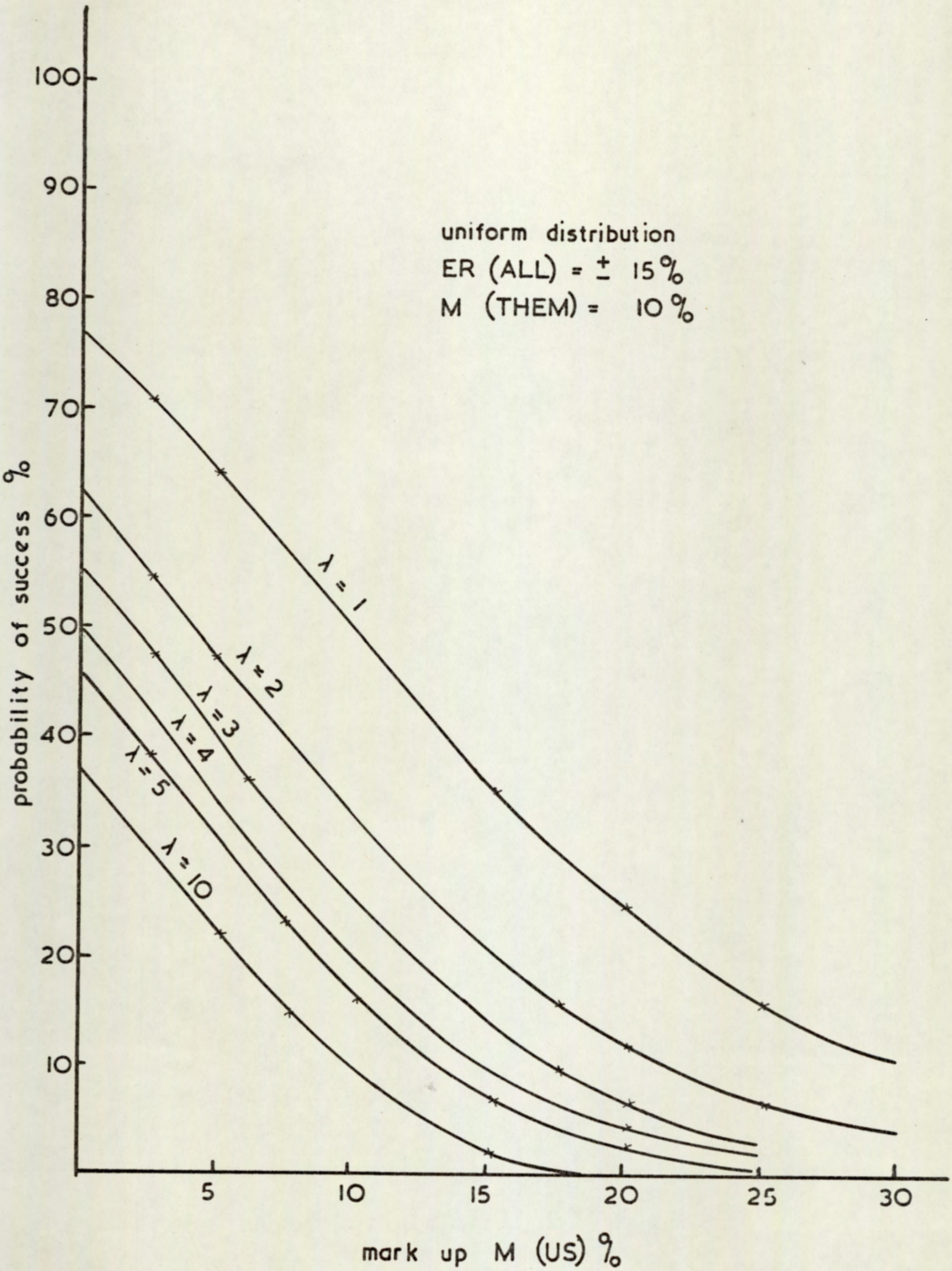

uniform distribution
ER (ALL) = ± 10 %
M THEM = 10 %
probability of success %
mark up M (US) %
λ = 1
λ = 2
λ = 3
λ = 4
λ = 5
λ = 10
0
5
10
15
20
25
10
20
30
40
50
60
70
80
90
100

Fig 5. 21.



uniform distribution
ER (ALL) = ± 15%
M (THEM) = 10%
probability of success %
100
90
80
70
60
50
40
30
20
10
λ = 1
λ = 2
λ = 3
λ = 4
λ = 5
λ = 10
5
10
15
20
25
30
mark up M (US) %

Fig. 5.22

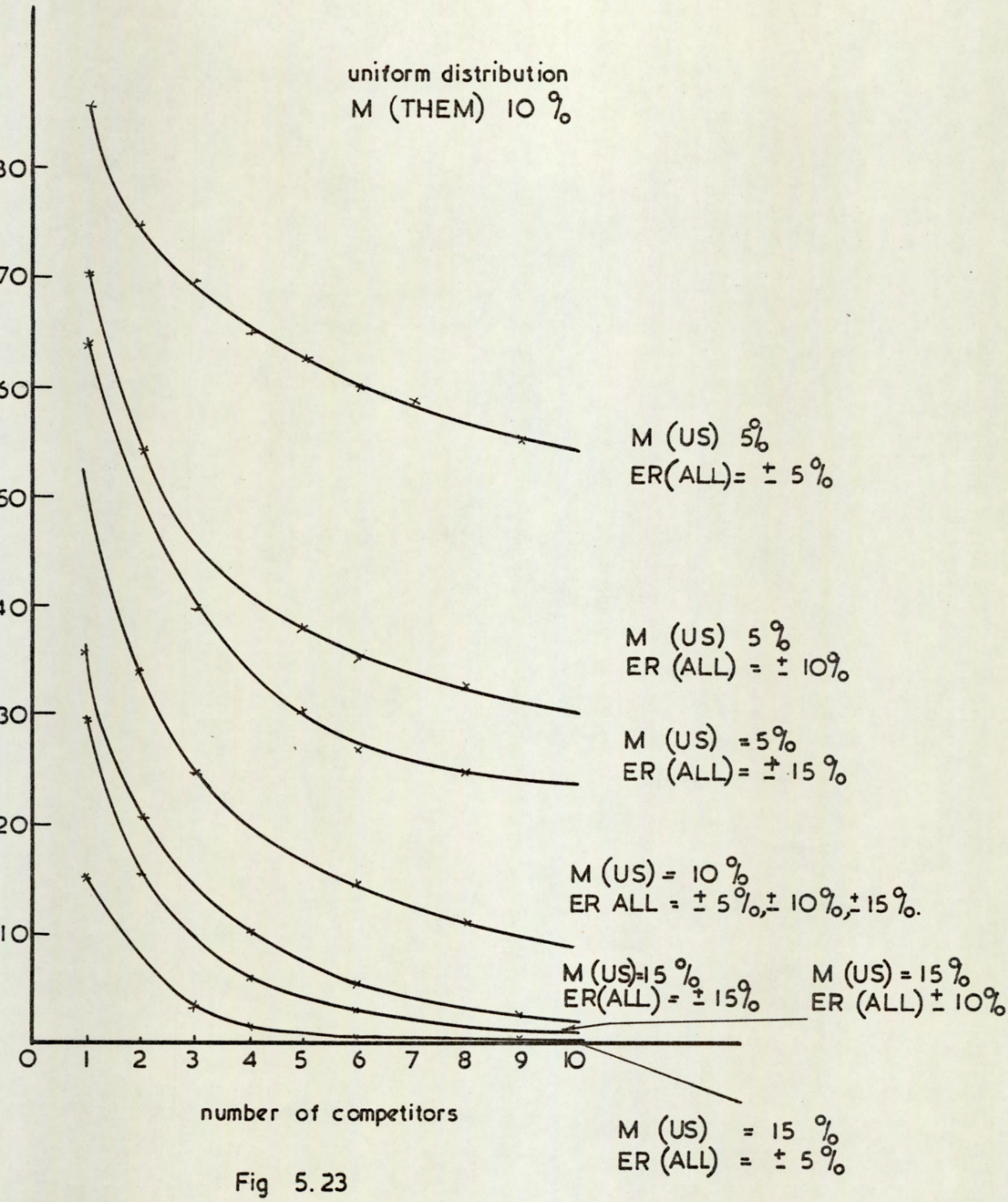

uniform distribution
M (THEM) 10 %
80
70
60
50
40
30
20
10
0
1
2
3
4
5
6
7
8
9
10
number of competitors
M (US) 5%
ER(ALL)= ± 5 %
M (US) 5 %
ER (ALL) = ± 10%
M (US) =5%
ER (ALL)= ± 15 %
M (US) = 10 %
ER ALL = ± 5 %,± 10%,± 15 %.
M (US)=15 %
ER(ALL) = ± 15%
M (US) = 15 %
ER (ALL) ± 10%
M (US) = 15 %
ER (ALL) = ± 5 %

Fig 5.23

5.4 Sampling the number of competitors and their mark-up:

In the previous simulation experiments, which will be referred to as simulation 1, the number of competitors was equal to four and their mark-up M(THEM) = 10% while M(US) was varied as 5%, 10%, and 15%. In a true bidding situation, the number of competitors and their mark-ups are not known to the contractor who can only control his own mark-up. A computer program, whose flow chart is presented in Appendix (7.2), was written to sample the number of competitors from a discrete distribution with limits ($2<\lambda<9$), where λ is the number of competitors. Each competitor's mark-up was sampled from a continuous distribution with the limits (0.0% < M(THEM) < 10.0%). This simulation experiment will be referred to as simulation 2. The subroutine RANDY was used to generate the PRN's required for the simulation and for convenience the distributions were assumed to be uniform.

It is noted that to conduct a true sensitivity analysis all variables are held constant except one, therefore the results of both simulation 1 and simulation 2 cannot be subjected to a strict sensitivity analysis. However to be able to draw conclusions regarding the effects of sampling M(THEM) and the number of competitors, simulation 2 results were compared with the case of 5 competitors from simulation 1.

The case of 5 competitors was chosen because it represents the average number of competitors when sampling between 2 and 9.

With reference to Table (5.3) it can be seen that in simulation 1 when the estimation accuracy is reduced from ±5% to ±15%, the success

TABLE (5.3)

			M (US) %					
			5		10		15	
			M (THEM) %					
			10	0-10	10	0-10	10	0-10
ER (ALL) %	±5	Success ratio	62.2	13.0	16.96	1.0	0.72	0
		ANP	3.2	1.94	6.06	4.867	9.87	-
	±10	Success ratio	38.7	19.0	16.9	5	4.26	1.0
		ANP	-0.838	-1.94	2.12	2.69	5.964	4.26
	±15	Success ratio	31.6	21	16.96	12	7.3	3.0
		ANP	-4.79	-5.7	-1.82	-1.17	1.79	3.94

NB=5

ratio decreases when M(US) = 5%, remain constant when M(US) = 10%, and increases when M(US) = 15%. However, in simulation 2, the success ratio increases with reducing the estimation accuracy for the three cases of M(US) = 5%, 10% and 15%. It is also noted that the success ratio value in simulation 2 is always less than that of simulation 1, with the difference being significant in the case M(US) = 5%.

It seemed logical that better comparison between simulation 1 and simulation 2 could be obtained if the means of the random variables in simulation 2 corresponded with the stationary values of simulation 1. Therefore, the M(THEM) range in simulation 2 was changed to (5% - 15%) to correspond to 10% in simulation 1 and the results of this case will be referred to as simulation 3 and are shown in Table (5.4).

It can be seen that the success ratio of simulation 3 for ER(ALL) of ±10% and ±15% corresponds to that of the mean number of competitors of simulation 1. However for ER(ALL) = ± 5% the success ratio of simulation 3 seems to depend on the mark-up M(US). Where M(US) = 5% it is less than that of 10 competitors of simulation 1. As M(US) increases to 10% and 15%, the success ratio of simulation 3 improves relative to that of simulation 1 and corresponds to the cases of 8 competitors and 5 competitors respectively.

The average net profit of simulation 3 must correspond to the average net profit of simulation 1 for the number of competitors which gives a similar success ratio to that of simulation 3. This is because

TABLE (5.4)

			SIMULATION 1 - M(THEM) = 10%								Simulation-3 M(THEM)=5-15%
ER(ALL)	M(US)	NB	3	4	5	6	7	8	9	10	3 - 10
		Suc.ratio	75.8	69.98	64.78	62.2	59.2	59.08	57.0	54.78	54.0
	5%	A.N.P.	4.01	3.65	3.42	3.2	3.08	2.97	2.82	2.76	2.825
		E(Profit)	3.04	2.55	2.2	1.99	1.82	1.75	1.60	1.51	1.52
		Suc.ratio.	33.36	24.8	19.66	16.96	14.2	12.68	10.9	9.74	13.0
	10%	A.N.P.	7.22	6.69	6.34	6.06	5.953	5.73	5.58	5.46	6.797
5%		E(Profit)	2.4	1.66	1.24	1.02	0.845	.727	.609	.53	.883
		Suc.ratio	6.44	2.72	1.10	.72	.24	.10	.10	.08	1.0
	15%	A.N.P.	10.88	10.48	10.27	9.87	9.73	9.60	9.60	9.6	9.633
		E(Profit)	.701	.285	.113	.07	.023	.009	.009	.007	.096
		Suc.ratio	54.86	46.98	41.5	38.7	35.16	34.4	33.08	31.32	39.0
	5%	A.N.P.	1.367	.332	-.35	-.838	-1.08	-1.43	-1.727	-1.83	-.932
		E(Profit)	.749	.156	-.145	-.324	-.38	-.49	-.57	-.57	-.363
		Suc.ratio	33.3	24.8	19.66	16.96	14.2	12.68	10.9	9.7	19.0
10%	10%	A.N.P.	4.4	3.3	2.68	2.12	1.9	1.46	1.17	.93	2.722
		E(Profit)	1.48	.84	.52	.35	.27	.18	.128	.09	.517
		Suc.ratio	16.12	10.04	6.2	4.26	2.86	1.86	1.48	.96	6.0
	15%	A.N.P.	7.89	7.06	6.46	5.964	5.87	5.46	5.18	5.23	7.89
		E(Profit)	1.27	.709	.40	.25	.16	.10	.07	.05	.473
		Suc.ratio	47.42	39.68	34.4	31.6	26.92	26.6	25.6	23.64	32.0
	5%	A.N.P.	-1.25	-2.78	-3.96	-4.79	-5.34	-5.69	-6.11	-6.30	-4.68
		E(Profit)	-.59	-1.1	-1.36	-1.48	-1.44	-1.5	-1.56	-1.489	-1.49
		Suc.ratio	33.3	24.8	19.66	16.96	14.2	12.68	10.9	9.74	21.0
15%	10%	A.N.P.	1.683	.092	-.97	-1.82	-2.14	2.79	-3.23	-3.59	-1.211
		E(Profit)	.561	.022	-.191	-.308	-.30	-.35	-.352	-.353	-.254
		Suc.ratio	20.98	14.16	10.02	7.3	5.32	4.0	3.42	2.62	12.0
	15%	A.N.P.	4.93	3.49	2.47	1.8	1.8	.747	.68	.371	3.314
		E(Profit)	1.035	.495	.247	.131	.096	.029	.023	.009	.397

M(US) and ER(ALL) are the same for both cases therefore the contractor makes the same amount of profit if he wins the contract.

Another way of analysing the results obtained by simulation 3 is to carry out a simple decision theory analysis. Assuming that the relevant decision model is that of Decision making under Uncertainty (DMUU), where the number, identification, and the frequencies of the environments (in this case ER) are unknowns, the appropriate criteria are:

A - The WALD CRITERION:- Which is the action of an extreme pessimist choosing the best of the worst.

B - The MAXIMAX CRITERION:- Which is the action of an extreme optimist choosing the best of the best.

C - The WEIGHTED MAXIMIN-MAXIMAX CRITERION:- Which is a compromise between A and B using an index of optimism.

D - The SAVAGE CRITERION:- Which minimizes regrets where a regret is defined as an opportunity cost.

E - The LAPLACE-BAYES CRITERION:- Which assumes that equal probabilities are allotted to the likelihood of each environment (i.e. ER).

Following is an application of these criteria to the results obtained from simulation 3.

MAXIMAX   MAXIMIN CRITERION

MATRIX OF EXPECTED PROFITS (M(THEM) 5 - 15%)

		ER(ALL)			(NB 3 - 10)				
		± 5%	± 10%	± 15%	MAXI MIN WORST	MAXI MAX BEST	1 - α ·6 x WORST	α ·4 x BEST	WEIGHTED OUTCOME
S1	5%	1.52	-.363	-1.49	-1.49	1.52	-.894	.608	-.286
M(US)									
S2	10%	.883	.517	-.254	-.254	.883	-.1524	.3532	+.201
S3	15%	.096	.473	.397	.096	.473	.0576	.1892	+.2468

(A) Maximin Criterion: choose S3 rank S3 $\succ$ S2 $\succ$ S1

(B) Maximax Criterion: choose S1 rank S1 $\succ$ S2 $\succ$ S3

(C) Weighted Maximin - Maximax Criterion: choose S3 rank S3 $\succ$ S2 $\succ$ S1. $\alpha = .4$

(α is Hurwicz's index of optimism, i.e. if $\alpha = 1.0$; subject is an extreme optimist, if $\alpha = 0$ subject is an extreme pessimist. Note similarity to Utility).

SAVAGE CRITERION

MATRIX OF REGRETS

ER(ALL)

		± 5	±10	±15	WORST
	S1	0	.880	1.887	1.887
M(US)	S2	.637	0	.651	.651
	S3	1.424	.044	0	1.424

check for intransitivity

				WORST	
S1	0	.880	1.744	1.744	S2 ≻ S1
S2	.637	0	0	.637	
S2	0	0	.651	.651	S2 ≻ S3
S3	.787	.044	0	.787	
S1	0	.836	1.887	1.887	S3 ≻ S1
S3	1.424	0	0	1.424	

(D) Savage Criterion (Minimise Regrets) S2 ≻ S3 ≻ S1.

Note that a check for intransitivity must be made - in this case the test is negative and the criteria can be used.

	Probabilities		.33	.33	.33	
				ER(ALL)		
			± 5	± 10	± 15	
	S1	5	.507	-.121	-.497	-.111
M(US)	S2	10	.294	.172	-.085	+.381
	S3	15	.032	.158	.132	+.322

(E) Laplace-Bayes Criterion: choose S2 rank S2 $\succ$ S3 $\succ$ S1

5.5 The break even mark-up (BEMU):

Fine, [30], and Whittaker, [8], studied the BEMU and presented different relationships between it and the number of competitors for uniformly distributed estimation accuracies of (± 5%, ±10%, and ±15%) as discussed in Section (3.5.1). In their study they assumed the mark-up to be constant for all contractors (4%-13% in Fine's case). The simulation results of the previous section were used to develop a similar relationship and to include the effect of varying the mark-up.

In the first stage, the case where all contractors apply the same mark-up (10%) and a uniformly distributed estimation accuracy was considered in order to check the results against those of Fine and Whittaker. The BEMU was calculated by subtracting the percentage average net profit, obtained by the computerised simulation, from the applied mark-up. These results are plotted with those of Fine and Whittaker in Fig. (5.24) where it can be seen that they are similar to Fine's when he assumes a mark-up of 10% for all contractors.

In the second stage, BEMU was calculated similar to the first stage but from the simulation results where the last contractor varies his mark-up relative to his competitors whose mark-ups are fixed at 10%. The results are presented in Figs. (5.25) to (5.27). The results are clearly different and hence justify the criticism of the previous models which do not include this possibility in their derivation. The first stage results and hence those of Fine and Whittaker can be considered as a special case of a more general field which is that of stage two.

As an example, the effect of the varying in mark-up M(US) on the BEMU for the ±5% estimation accuracy will be discussed. With reference to fig. (5.25), and when all contractors have the same mark-up (10%), the increase in the BEMU when the number of competitors was increased from 1 to 10 is 135%. If the mark-up of all competitors, M(THEM) remains at 10% and that of the last one M(US) is taken as 5% this increase becomes 318% while if M(US) is 15% it becomes 12% only. Another way of looking at the variation is that the increase in BEMU when M(US) is increased from 5% to 10% and then to 15% with one competitors is 83%, and 31% respectively. These values become 89% and 22% when the number of competitors is 10.

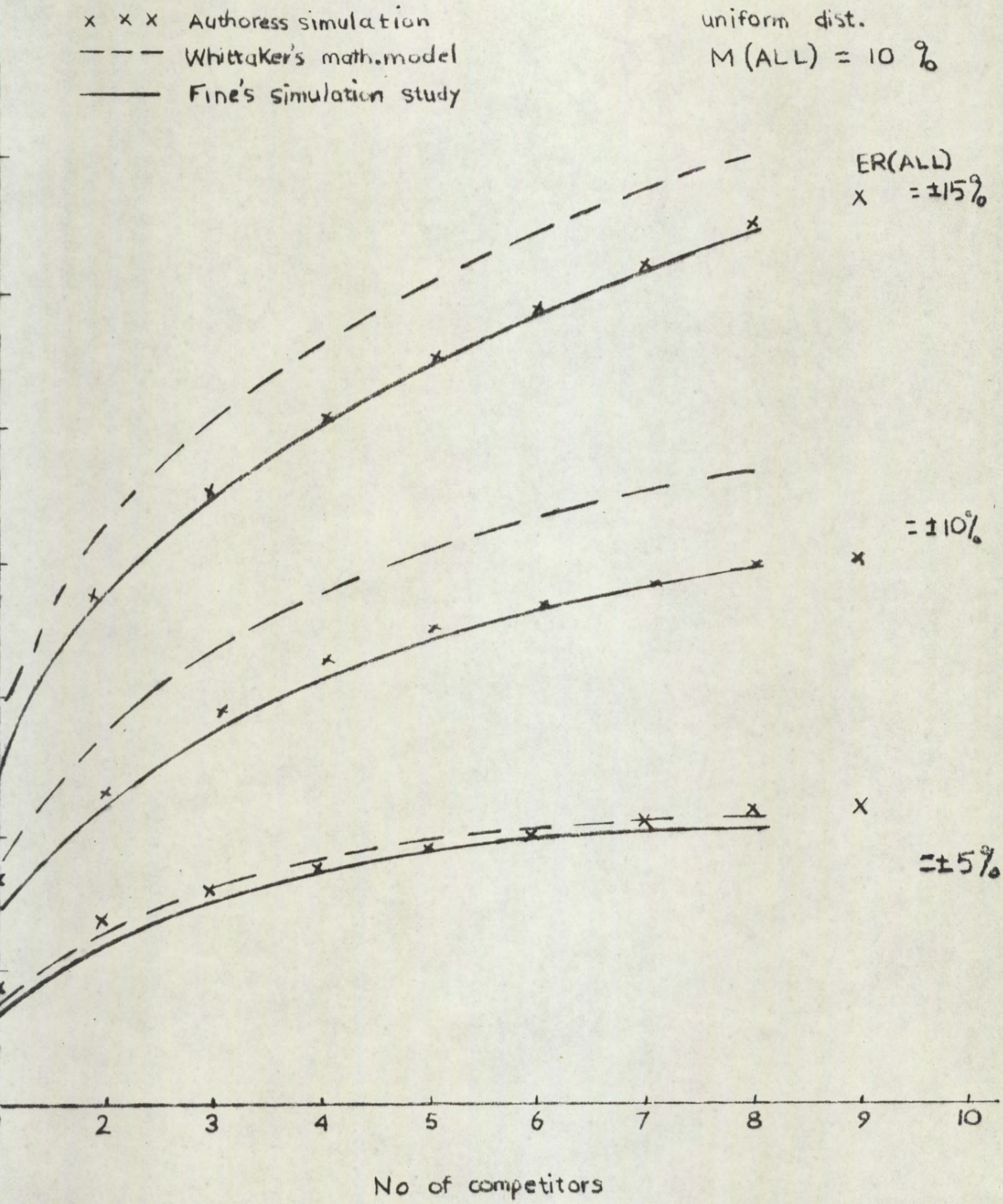
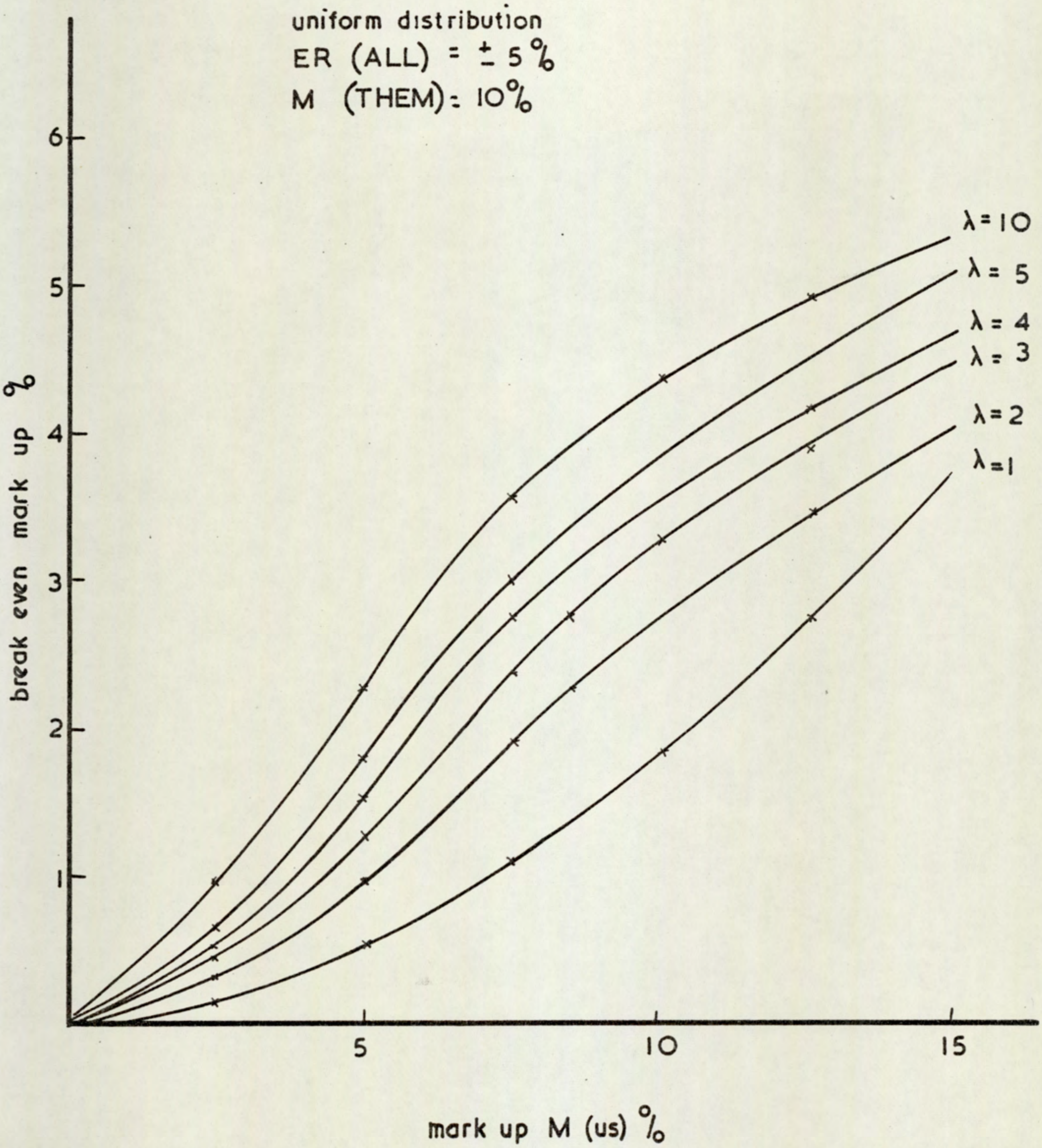

x x x Authoress simulation
--- Whittaker's math.model
—— Fine's simulation study
uniform dist.
M (ALL) = 10 %
ER(ALL)
= ±15%
= ±10%
= ±5%
2
3
4
5
6
7
8
9
10
No of competitors

Fig. 5.24



uniform distribution
ER (ALL) = ± 5%
M (THEM) = 10%
break even mark up %
mark up M (us) %
λ = 10
λ = 5
λ = 4
λ = 3
λ = 2
λ = 1
1
2
3
4
5
6
5
10
15

Fig 5.25

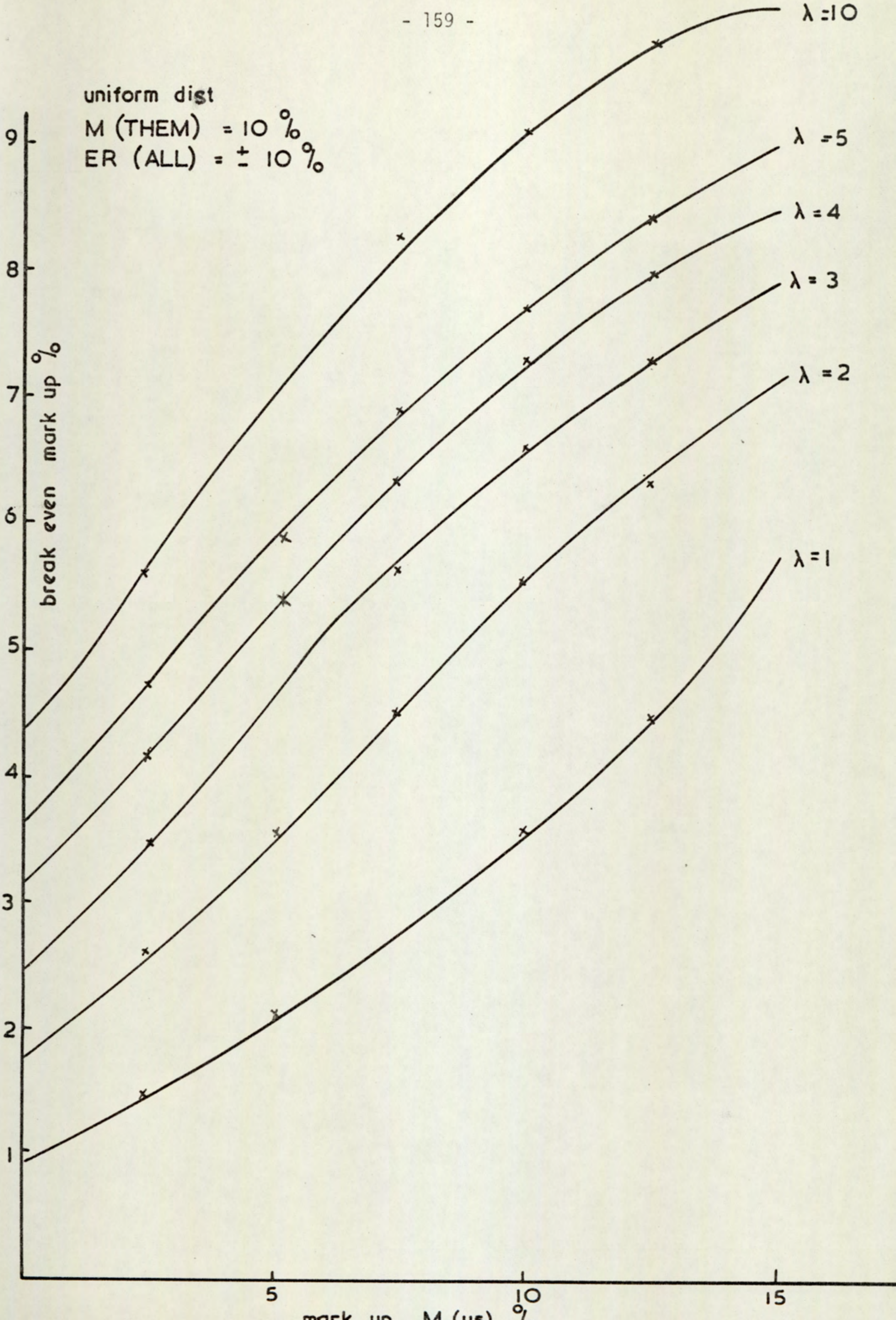

uniform dist
M (THEM) = 10 %
ER (ALL) = ± 10 %
break even mark up %
mark up M (us) %
λ =10
λ =5
λ =4
λ = 3
λ = 2
λ =1
1
2
3
4
5
6
7
8
9
5
10
15

Fig . 5. 26

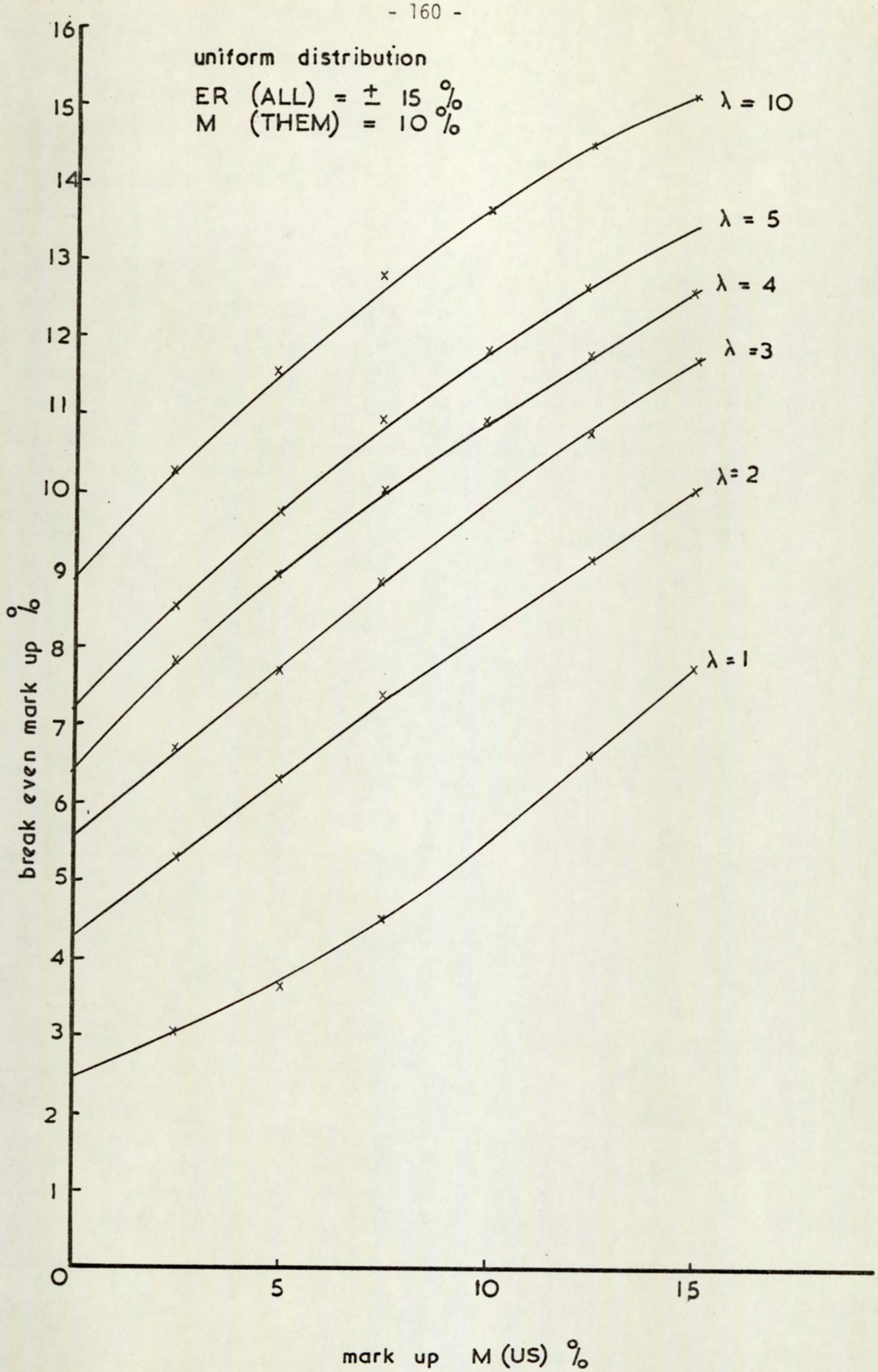

uniform distribution
ER (ALL) = ± 15 %
M (THEM) = 10 %
λ = 10
λ = 5
λ = 4
λ =3
λ= 2
λ = 1
break even mark up %
mark up M (US) %
0
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
5
10
15

Fig . 5.27

5.6 The effect of the job value

In all the previous simulation experiments, the job value was fixed at a hypothetical figure of 100. For the results to reflect true bidding situations, where the job value is a variable, it was thought desirable to investigate the effects of varying the job value on the simulation results. The various aspects of this study are discussed subsequently.

5.6.1 Data Generation

In order to cover a reasonable range of the market a computerised method, using pseudo random numbers generated by the subroutine developed and tested previously, was used to sample job values from a uniform distribution between £50k and £1000k. As this subroutine has one stream, the PRN's required for sampling the estimation error were generated by using the standard NAG library routine, which is available at the University Computer Centre and statistically tested in Appendix (7.1). The job values generated were assumed to be the true tender cost without taking the estimation accuracy or the mark-up into consideration.

5.6.2 The computerised simulation

The number of bidders was taken to be (5). Their estimation accuracy of ±10% to ±5% with intervals of ±1% uniformly and normally distributed ($3\sigma = \pm ER$) were applied together with a mark-up of 10%. From the experience gained in applying the computerised simulation to fixed job value tenders it was found that at least 500 simulations need to be considered for the method to yield good results. As it is not possible in the true situation to bid for 500 tenders per year, the study was conducted to cover 10 years with 50 tenders bid for at each one. The flow chart of the program is presented in Appendix (7.2) and its output includes the following information:

1. The sum of the true cost of the 50 contracts per year bid for by the 5 bidders.
2. The sum of the true cost of the contracts won by each contractor per year.
3. By subtracting the true tender cost from that after applying the estimation errors and mark-up, the net profit achieved by each winner is obtained and the sum of it per year is outputed.
4. The sum of profit in step 3 is divided by the number of contracts won for each contractor to give the average profit per contract per year for that particular contractor.
5. The percentage success of each contractor per year is calculated from the number of bids he won divided by the ones he bid for i.e. 50.

The results are shown in Fig. (5.28) to (5.31) and Tables (5.5) to (5.8).

5.6.3 The simulation results:

A. The success ratio:

By averaging the success ratios of the five bidders over 10 years they were found to be the same as those obtained with the fixed job value simulation i.e. 20%. This is expected as all the competitors are applying the same tendering policy (estimation accuracy and mark-up) therefore they all stand the same chance of winning and the job value has no bearing on it. These results are shown in Tables (5.5) to (5.8).

B. The Break even mark-up

By averaging the profit sum over 10 years for each contractor and dividing it by the same average of the sum of contracts won by him, an average net profit over the 10 years period is obtained. As the intended profit per cent was 10% (mark-up), the difference between it and the value obtained is the break even mark-up, as shown in Tables (5.9) and (5.10). This value for an estimation accuracy of ±10% uniformly distributed was 7.3%, and 4.4% for the case of ±10% estimation accuracy normally distributed.

By comparing these results with Fine's and Whittaker's, it was seen that the first corresponds to Whittaker's model while the second one corresponds to Fine's. However both models do not consider mark-ups or varying job values and only yield similar results for ±5% estimating accuracy. However, the method for determining the break even mark-up used in this simulation can be considered more realistic.

C. The average net profit

The average net profits were evaluated in the previous section. In the fixed job value situation, when the estimation accuracy and mark-up are the same for all contractors, their average net profits are identical. However, for a variable job value, even if the estimation accuracy and mark-up are the same, the average net profits of the contractors differ slightly. By averaging them for the five contractors comparisons can be made with the fixed job value cases, which are obtained from Figs.(5.6) and (5.7). These averages are obtained from Tables (5.9) and (5.10) and shown in Table (5.11). It can be seen that the average net profits are very similar in the variable and fixed job value situations and hence it can be concluded that the job value has no effect on them.

D. The overall profit

Neal, [29], suggested that an improvement of the normally distributed estimation accuracy from ±10% to ±5% will result in increasing the overall profit by 40% . The run with ±5% estimation accuracy was checked with ±10% run and the improvement was found to be 39.4% . This result corresponds to 38% in the fixed job value case as shown in Section (5.2). When the error was assumed to be uniformly distributed the improvement was 120%. This is expected as the normal distribution gives a lower chance of a bad estimate than the uniform one and the winner is the one with the greatest inaccuracy when the mark-up is constant. By plotting the increase in overall profit, as the estimation accuracy is reduced with respect to that obtained from

±10%, it was found that the relation is nearly linear, as shown in figures (5.32, 5.33) and Table (5.12). However, the increase in average net profit, per contract won, is less than that of the overall profit. This is thought to be because some contracts are won with very little profit and hence offsetting the average, i.e. the increase in the total profit is not shared evenly by all contracts won.

TABLE (5.5)

SUM OF CONTRACTS WON

BN \ Yr	1	2	3	4	5	6	7	8	9	10	10 year Average
1	5110745	7861101	1284434	4444951	3660682	4867722	1747041	5169083	1999898	4827583	4097324.0
2	3085391	4621228	4339334	2627910	2213198	6374377	5770350	2577689	6809963	4080619	4250005.9
3	5238830	4099029	3638865	5238316	7664987	5560262	3988085	4140233	4916580	3059807	4754499.4
4	6514306	3770190	6736332	4035132	5901531	4620401	4200326	8368746	7749918	5475236	5737211.8
5	8077003	3703676	10943949	6723895	5561928	5891129	5608083	6614915	4910608	7681657	6571684.3
						PROFIT SUM					
1	333901	515861	80748	273387	209380	324151	151500	360319	123727	318465	269143.4
2	185397	261886	294585	131564	123820	371348	379151	206769	385694	256462	259667.6
3	328833	261479	220707	321136	470120	378562	258070	239866	322516	193444	299473.3
4	439966	252065	411517	288727	331980	286805	248604	513968	493207	395802	366264.1
5	515856	230081	666442	405464	319010	345656	316359	440058	294849	548020	408179.5
						AVERAGE NET PROFIT/CONTRACT WON					
1	30354	39681	20185	30376	23264	36016	18937	40035	30931	28951	29873.0
2	30899	21823	32731	21927	24764	37134	34468	25846	32141	36637	29837.0
3	36537	32684	24523	29194	36163	31546	25807	39977	32251	27634	31631.6
4	43996	31508	34293	26247	25536	31867	22600	36712	37939	39580	33027.8
5	36846	25564	41652	31189	31901	34565	31635	33850	26804	36534	33054.0
						SUCCESS RATIO					
1	22	26	8	18	18	18	16	18	8	22	17.4
2	12	24	18	12	10	20	22	16	24	14	17.2
3	18	16	18	22	26	24	20	12	20	14	19.0
4	20	16	24	22	26	18	22	28	26	20	22.2
5	28	18	32	26	20	20	20	26	22	30	24.2

Uniform distribution M = 10%, ER = ±5%

TABLE (5.6)

SUM OF CONTRACTS WON

BN \ Yr	1	2	3	4	5	6	7	8	9	10	10 year Average
1	4637280	6925887	5197488	4723481	2975078	4644595	4340566	5688239	6996772	4255482	5038486.8
2	3589738	1989425	5279585	5499039	5895899	5740242	4507008	4881529	4785132	3701552	4586914.9
3	9617615	4954495	6571384	6281756	6125201	5041491	5335098	3222377	4240516	2284771	5367470.4
4	3417970	4445479	2910383	3029351	4169841	6074488	2678101	4751349	2776405	6680407	4093377.4
5	6768172	5739938	6984073	3536575	5836306	5813076	4453112	8327173	7588144	8202689	6324925.8
					PROFIT SUM						
1	366407	565381	425635	395285	248625	351882	341371	434601	531041	344235	400446.3
2	295353	161652	400599	429007	473117	464902	350093	394664	407041	301892	367832.0
3	789361	369294	534263	515648	483807	367380	453294	244250	310941	196529	426476.7
4	249477	367688	240843	221043	308679	498853	176287	400067	218776	527866	320957.4
5	524397	442114	525473	289549	426045	437583	362303	674921	569304	694090	494577.9
					AVERAGE NET PROFIT/CONTRACT WON						
1	45800	40384	42563	43920	49725	35188	37930	33430	37931	43029	40990.0
2	49225	40413	44511	35750	39426	51655	29174	43851	45226	37736	41696.7
3	49335	33572	38161	46877	40317	36738	34868	48850	31094	28075	38788.7
4	31184	45961	34406	24560	34297	41571	44070	66677	43755	40605	40708.6
5	43699	34008	52547	32172	35503	48620	30191	39701	47442	49577	41346.0
					SUCCESS RATIO						
1	16	28	20	18	10	20	18	26	28	16	20.0
2	12	8	18	24	24	18	24	18	18	16	18.0
3	32	22	28	22	24	20	26	10	20	14	21.8
4	16	16	14	18	18	24	8	12	10	26	16.2
5	24	26	20	18	24	18	24	34	24	28	24.0

Normal Distribution, 3σ M = 10%, ER = ±5%

TABLE (5.7)

SUM OF CONTRACTS WON

BN \ Yr	1	2	3	4	5	6	7	8	9	10	10 year Average
1	3514396	4508935	3964340	5246955	5170504	5960347	2716350	6103095	6399550	4452452	4803692.4
2	4744007	5349658	6857996	7058691	2691728	4612682	5178666	2799671	6115619	6551177	5195989.5
3	7655202	6626243	2815240	4859641	7456871	6719133	8124491	7745671	4322570	4767150	6109221.2
4	6176074	3153631	3561892	2481792	3630943	5383492	3231807	5128314	6481574	3851142	4308066.1
5	5936596	4416756	9743445	3423124	6052280	4638238	2062571	5093915	3067656	5502981	4993756.2
					PROFIT SUM						
1	135016	182078	146106	50860	85620	119980	95265	202780	182675	109132	130951.2
2	23972	107810	219548	179325	39662	105550	149446	77299	237115	205394	134512.1
3	105853	285139	54401	101136	226590	139071	209585	115067	69126	125089	143105.7
4	102341	86925	104501	26464	189333	175924	77708	187216	137637	187293	127534.2
5	231179	203173	247293	162413	166022	223755	47468	254480	112040	191468	183929.1
					AVERAGE NET PROFIT/CONTRACT WON						
1	19288	18207	18263	5086	9513	9229	8660	20278	15222	10913	13465.9
2	2996	10781	15682	13794	5666	15078	13586	11042	21555	14671	12485.1
3	10585	20367	9066	10113	14161	10697	13099	8851	6912	12508	11635.9
4	8528	9658	13062	3308	27047	19547	11101	17019	12512	23411	14519.3
5	17783	29024	17663	18045	15092	27969	9493	28275	18673	23933	20595.0
					SUCCESS RATIO						
1	14	20	16	20	18	26	22	20	24	20	20.0
2	16	20	28	26	14	14	22	14	22	28	20.4
3	20	28	12	20	32	26	32	26	20	20	23.6
4	24	18	16	16	14	18	14	22	22	16	18.0
5	26	14	28	18	22	16	10	18	12	16	18.0

Uniform Distribution M = 10%, ER = ±10%

TABLE (5.8)

SUM OF CONTRACTS WON

BN \ Yr	1	2	3	4	5	6	7	8	9	10	10 year Average
1	4996445	3025067	5722941	5920150	7220545	4512080	5695204	3894528	7275926	4474058	5273694.4
2	8543950	3129481	4996627	3896594	4848994	6316764	2525852	5595573	4222287	3084109	4716023.1
3	4475261	3907915	5082036	4230245	4695272	3575235	5615970	5747280	6177850	8924887	5243195.1
4	7351616	7973640	4250184	4606840	3052827	7030960	3475975	5565574	7164337	3453405	5392535.8
5	2659004	6019121	6891126	4416373	5184688	5878852	4000885	6067711	1546570	5188443	4785277.3
						PROFIT SUM					
1	349219	164832	361060	341449	426130	233701	308939	232231	447301	290465	315532.7
2	542950	208046	228337	100409	292934	398452	121167	269951	265802	155062	258311.0
3	269310	186459	206739	205919	199237	179075	382291	429265	305145	536962	290040.2
4	465645	439207	221178	239318	241621	296165	182807	310476	375066	183182	295466.5
5	176366	435910	388320	294004	292738	251094	226801	400589	78804	319204	286383.0
						AVERAGE NET PROFIT/CONTRACT WON					
1	38802	20604	32823	31040	28408	38950	22067	33175	29823	36308	31199.7
2	49359	23116	22833	12551	29293	30650	24233	24541	37971	19382	27392.9
3	29923	31076	20673	25739	22137	29845	27306	35772	27743	31586	28179.7
4	33260	31371	27647	26590	40270	26924	20311	34497	26793	26168	29382.8
5	25195	33531	35301	21000	29273	17935	28350	36417	26265	31920	28519.0
						SUCCESS RATIO					
1	18	16	22	22	30	12	28	14	30	16	20.8
2	22	18	20	16	20	26	10	22	14	16	18.4
3	18	12	20	16	18	12	28	24	22	34	20.4
4	28	28	16	18	12	22	18	18	28	14	20.2
5	14	26	22	28	20	28	16	22	6	20	20.2

Normal Distribution M = 10%, ER = ±10%

TABLE (5.9)

Bidder No.	Uniform Distribution, M = 10%, ER = ±10%			
	Profit sum	Sum of contract won	Average net profit	BEMU
1	130951.2	4803692.4	2.726	7.274
2	134512.1	5195989.5	2.588	7.412
3	143105.7	6109221.2	2.342	7.658
4	127534.2	4308066.1	2.960	7.04
5	183929.1	4993756.2	3.683	6.317
			M = 10%, ER = ±5%	
1	269143.4	4097324.0	6.568	3.432
2	259667.6	4250005.9	6.109	3.891
3	299473.3	4754499.4	6.298	3.702
4	366264.1	5737211.8	6.384	3.616
5	408179.5	6571684.3	6.211	3.789

TABLE (5.10)

Bidder No.	Normal Distribution, M = 10%, ER = ±10%			
	Profit sum	Sum of contract won	Average net profit	BEMU
1	315532.7	5273694.4	5.983	4.017
2	258311.0	4716023.1	5.477	4.523
3	290040.2	5243195.1	5.531	4.469
4	295466.5	5392535.8	5.479	4.521
5	286383.0	4785277.3	5.984	4.016
			M = 10%, ER = ±5%	
1	400446.3	5038486.8	7.947	2.053
2	367832.0	4586914.9	8.019	1.981
3	426476.7	5367470.4	7.945	2.055
4	320957.4	4093377.4	7.840	2.160
5	494577.9	6324925.8	7.819	2.181

TABLE (5.11)

ER%	Average net profit: Fixed job value	Average net profit: Variable job value
Uniform Distribution		
± 5	6.34	6.314
± 10	2.686	2.856
Normal Distribution		
± 5	7.843	7.914
± 10	5.686	5.690

TABLE (5.12)

Normal Distribution

ER Estimating accuracy	Total profit ratio	Percentage increase
10%	1	0%
9%	1.11	11%
8%	1.15	15%
7%	1.22	22%
6%	1.30	30%
5%	1.394	39.4%

Uniform Distribution

ER Estimating accuracy	Total profit ratio	Percentage increase
10%	1	0%
9%	1.18	18%
8%	1.5	50%
7%	1.71	71%
6%	1.896	90%
5%	2.2	120%

$$\text{Total profit ratio} = \frac{\text{Profit sum at accuracy } (\pm ER)}{\text{Profit sum at accuracy } (\pm 10\%)}$$

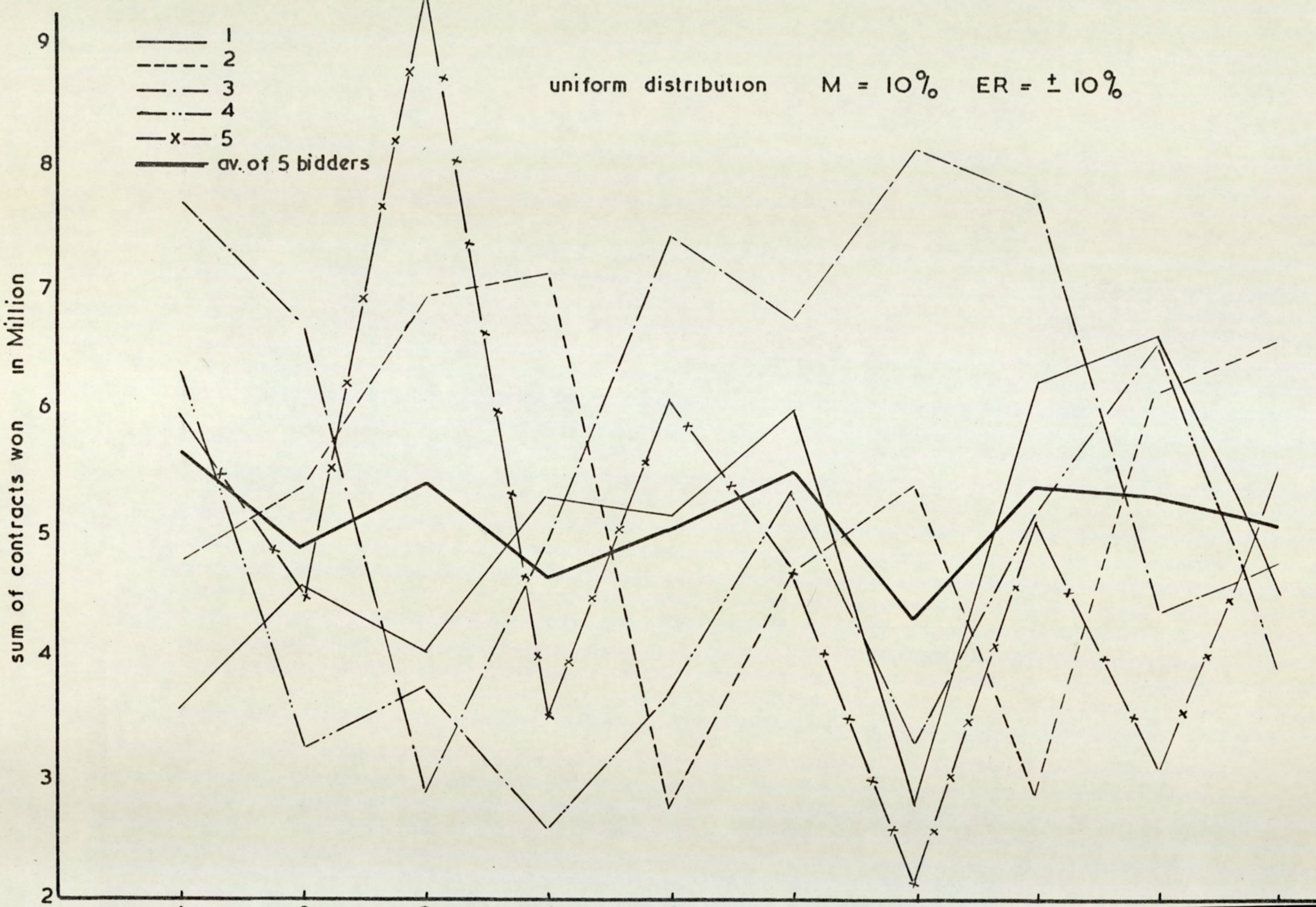

uniform distribution M = 10% ER = ± 10%
1
2
3
4
5
av. of 5 bidders
sum of contracts won in Million
9
8
7
6
5
4
3
2

Fig. 5.28

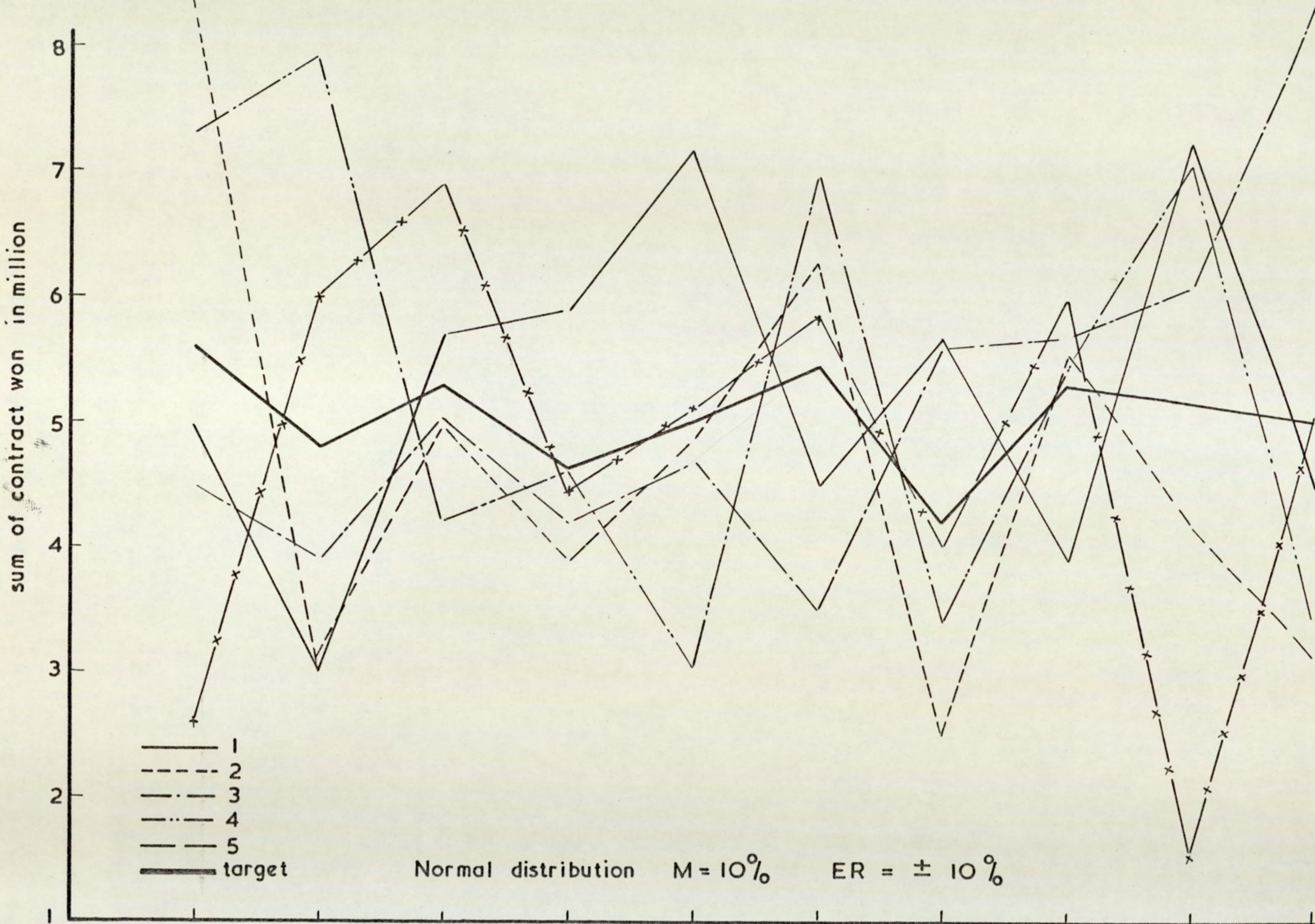

sum of contract won in million
8
7
6
5
4
3
2
1
1
2
3
4
5
target
Normal distribution M = 10% ER = ± 10 %

Fig. 5.29

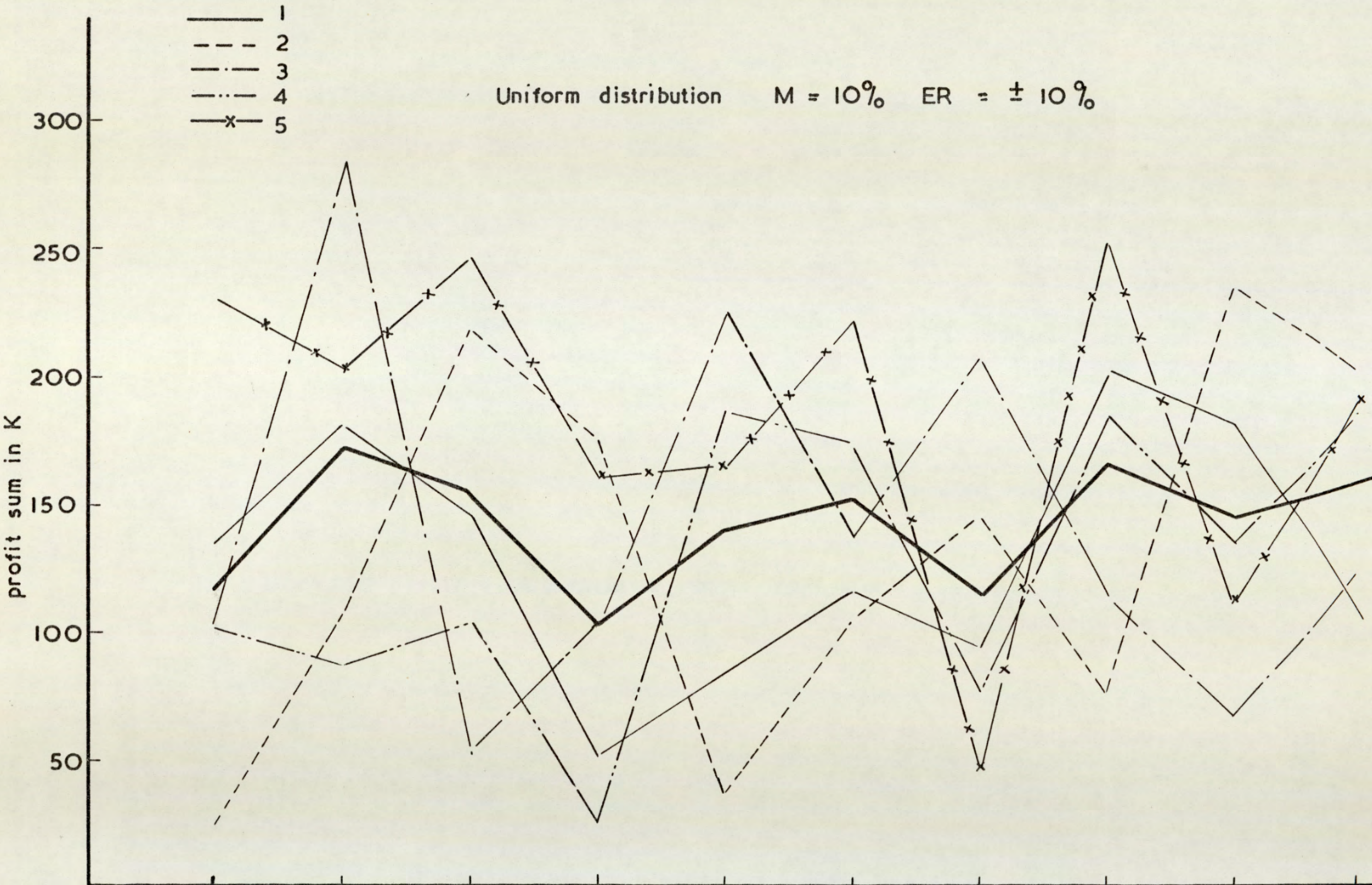

1
2
3
4
5
Uniform distribution M = 10% ER = ± 10%
300
250
200
150
100
50
profit sum in K

Fig. 5.30

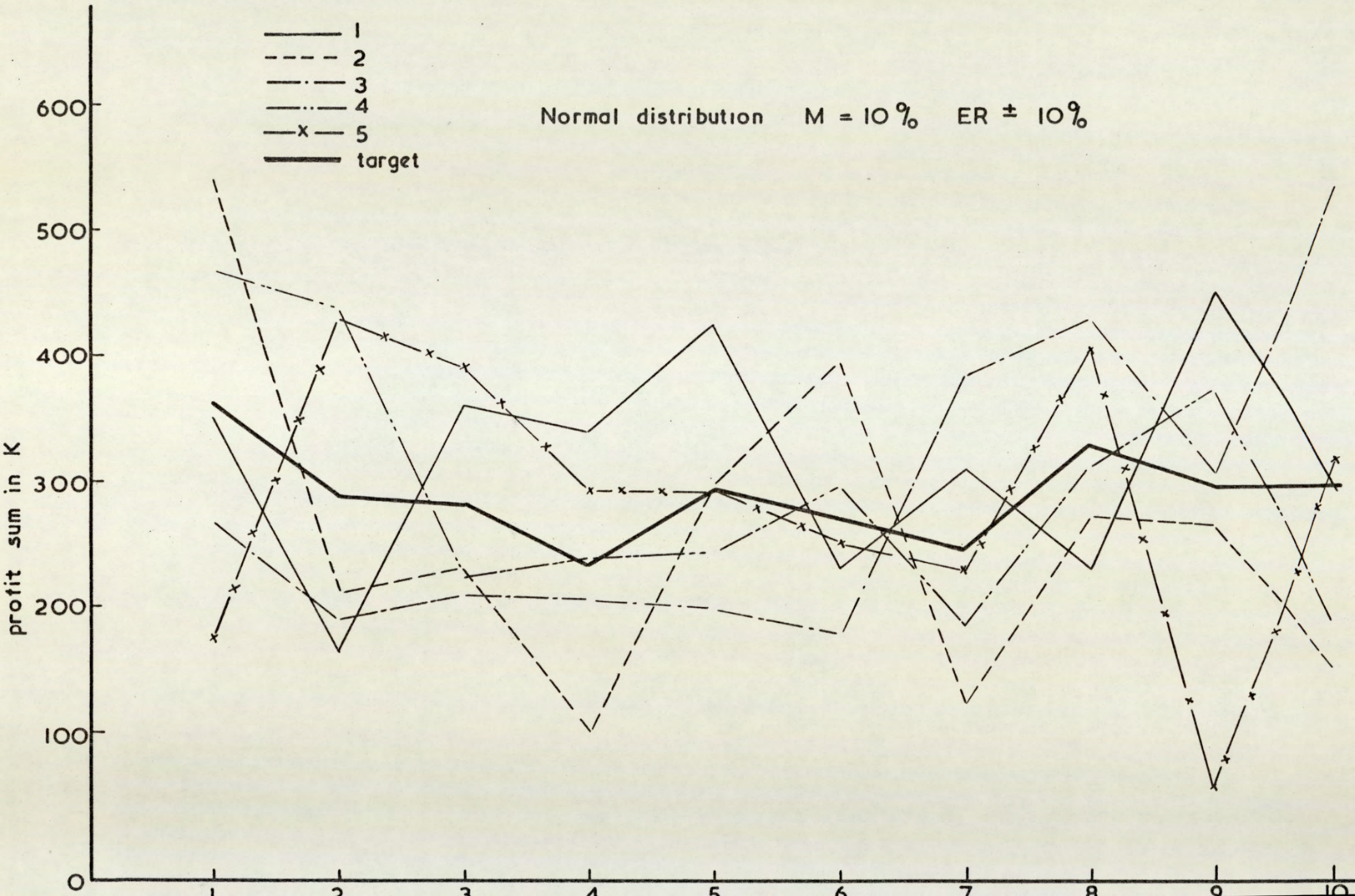

1
2
3
4
5
target
Normal distribution M = 10% ER ± 10%
profit sum in K
600
500
400
300
200
100
0
1
2
3
4
5
6
7
8
9
10 yrs

Fig. 5.31

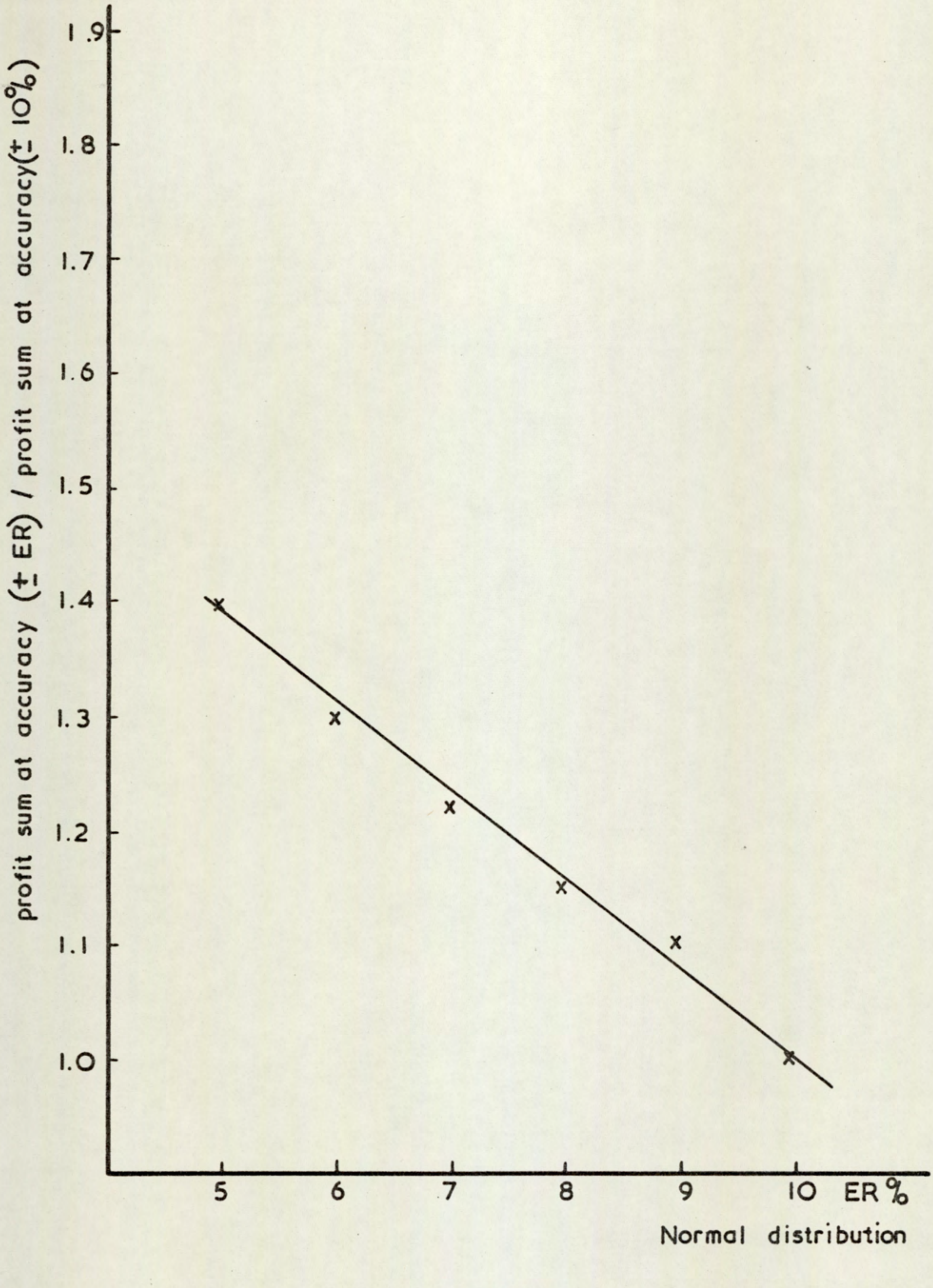

profit sum at accuracy (± ER) / profit sum at accuracy(± 10%)
1.9
1.8
1.7
1.6
1.5
1.4
1.3
1.2
1.1
1.0
5
6
7
8
9
10
ER%
Normal distribution

Fig. 5.32

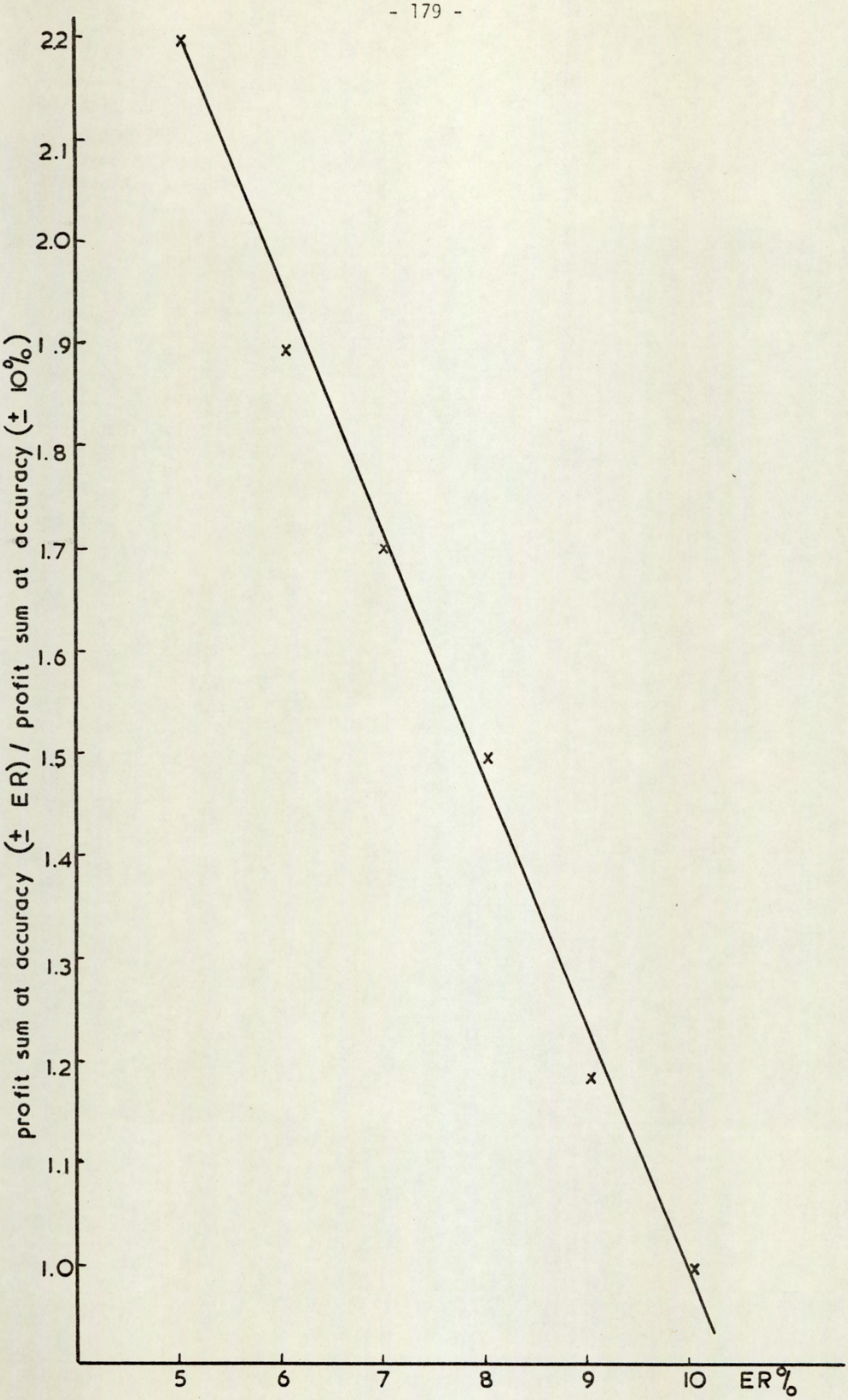

profit sum at accuracy (± ER) / profit sum at accuracy (± 10%)
2.2
2.1
2.0
1.9
1.8
1.7
1.6
1.5
1.4
1.3
1.2
1.1
1.0
5
6
7
8
9
10
ER%
uniform distribution

Fig. 5.33

5.7 Application of the concept of target probability

It was found from the previous section that the resulting annual work load of a contractor may be as far as ±100% from his annual average for certain years. As no contractor can handle such a variation, Trimble's target probability concept, [10], discussed in Section (3.2.3) was applied to influence the work gained. The relation between the success ratio and the applied mark-up is presented in Fig. (5.3) with ±10% estimation accuracy. For convenience the curve was approximated to a straight line and is shown in Fig. (5.34). From the previous section an average value for the annual available work was found and each contractor's annual target was set at 20% of that value.

The intervals at which the obtained work is compared with the target value were 1 year, 6 months, 3 months, and 6 weeks. These time intervals are much longer than the ones suggested by Trimble in his method but are necessary to keep a reasonable number of simulations in each interval.

The results are shown in Figs.(5.35) to (5.38). The important conclusions which can be drawn from them is that it is better to apply a fixed mark-up policy rather than alter it for a long interval as seen in the case of one year. The results improve as the period is reduced to 6 months and 3 months respectively, but the trend starts to reverse in the 6 weeks case. It is expected, intuitively, that results improve with reducing the time interval and its failure to do so in the six weeks case is attributed to the number of simulations in this period. If the case of a contractor who exceeds his target in the first six weeks is considered, he will apply a higher mark-up to reduce his volume of work. The number of simulations is so few (12) that he might not get any job and hence reduce his mark-up drastically for the third stage and gain still more work. This can work against a contractor by reducing his work volume also. To obtain good simulation results the number of simulations must be increased to a much higher level which then will not reflect a true bidding situation.

This method is concerned with maintaining a stable level of work load to the contractor without taking into account the price he pays for obtaining this work. By reducing the mark-up to become more competitive, the contractor risks taking jobs at a loss. For the best distribution of work load achieved, i.e. comparing every 3 months with the target, the values of the total net profit of each contractor were plotted for every year in Fig. (5.39). It can be seen that each contractor had a certain number of years in which he was operating at a loss and the average of the five contractors profits for each year is less than that of the fixed mark-up policy shown in Fig. (5.28).

A modification to the theory can be made to safeguard against losses by setting a minimum limit to the chosen mark-up. The value of this limit and that of the optimum checking time period can be the subject of an independent investigation due to their importance and originality.

A computer program flow chart for this simulation experiment is presented in Appendix (7.2).

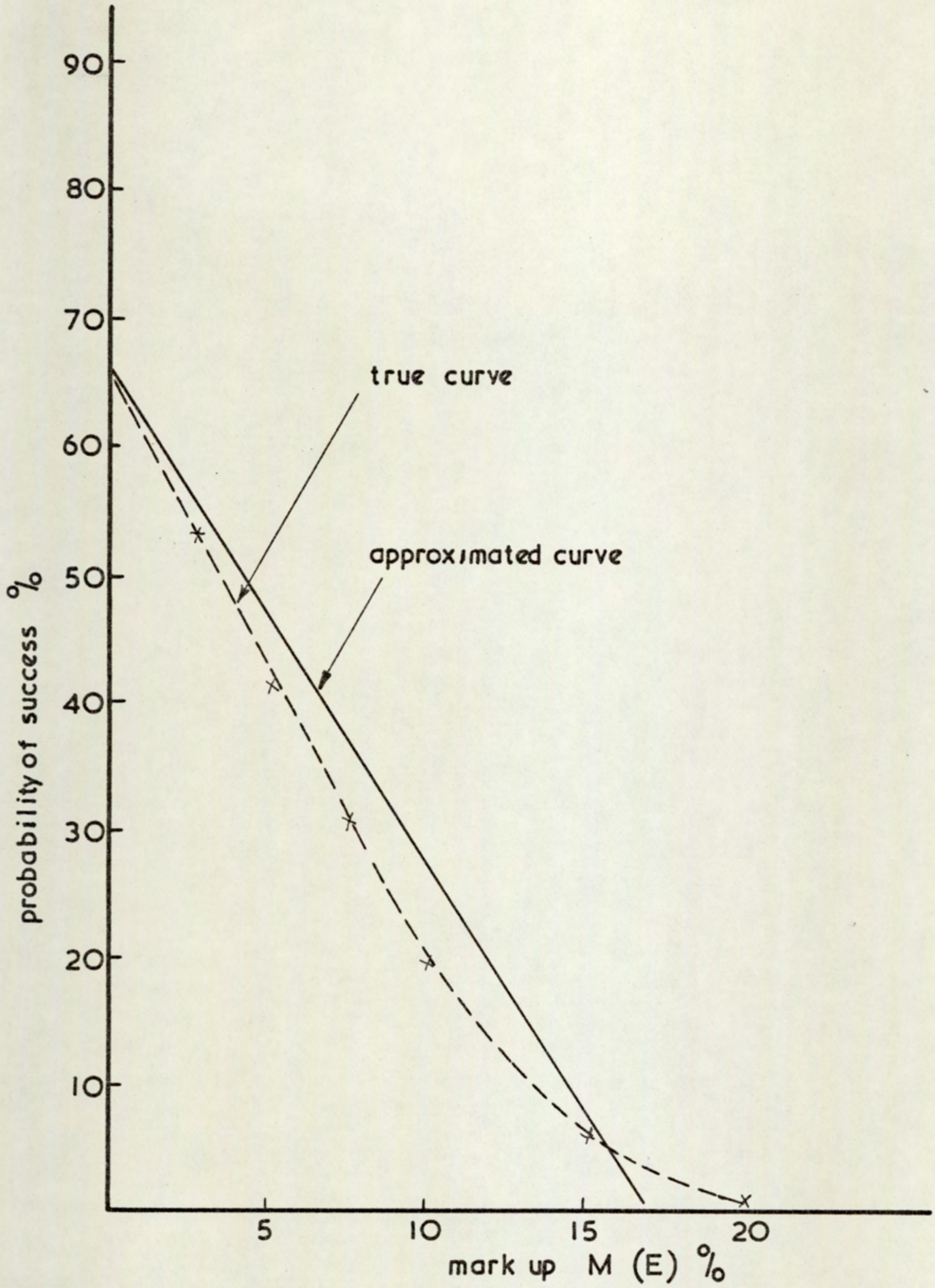

90
80
70
60
50
40
30
20
10
probability of success %
true curve
approximated curve
5
10
15
20
mark up M (E) %

Fig 5.34

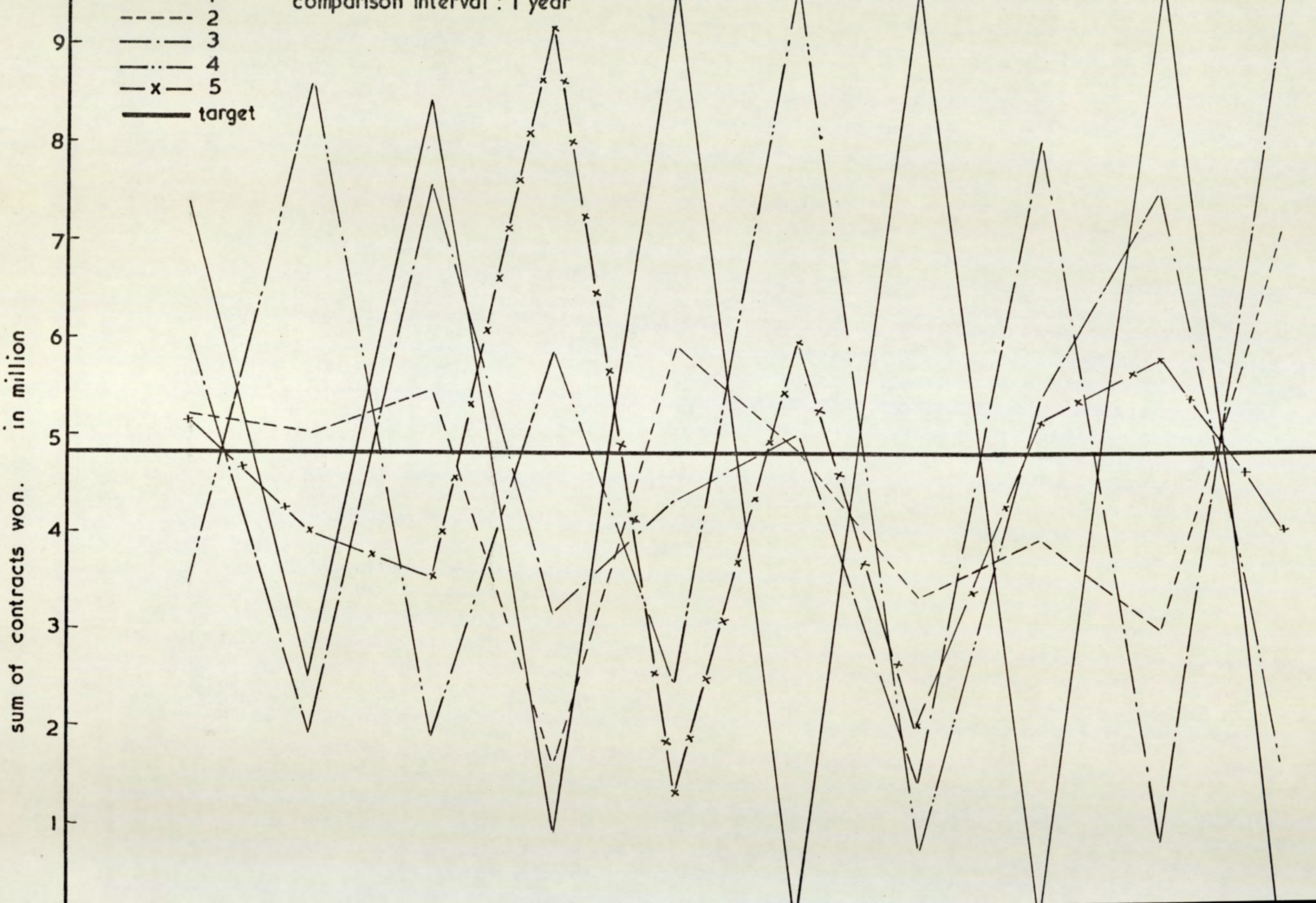

comparison interval : 1 year
2
3
4
5
target
sum of contracts won. in million
9
8
7
6
5
4
3
2
1

Fig. 5. 35

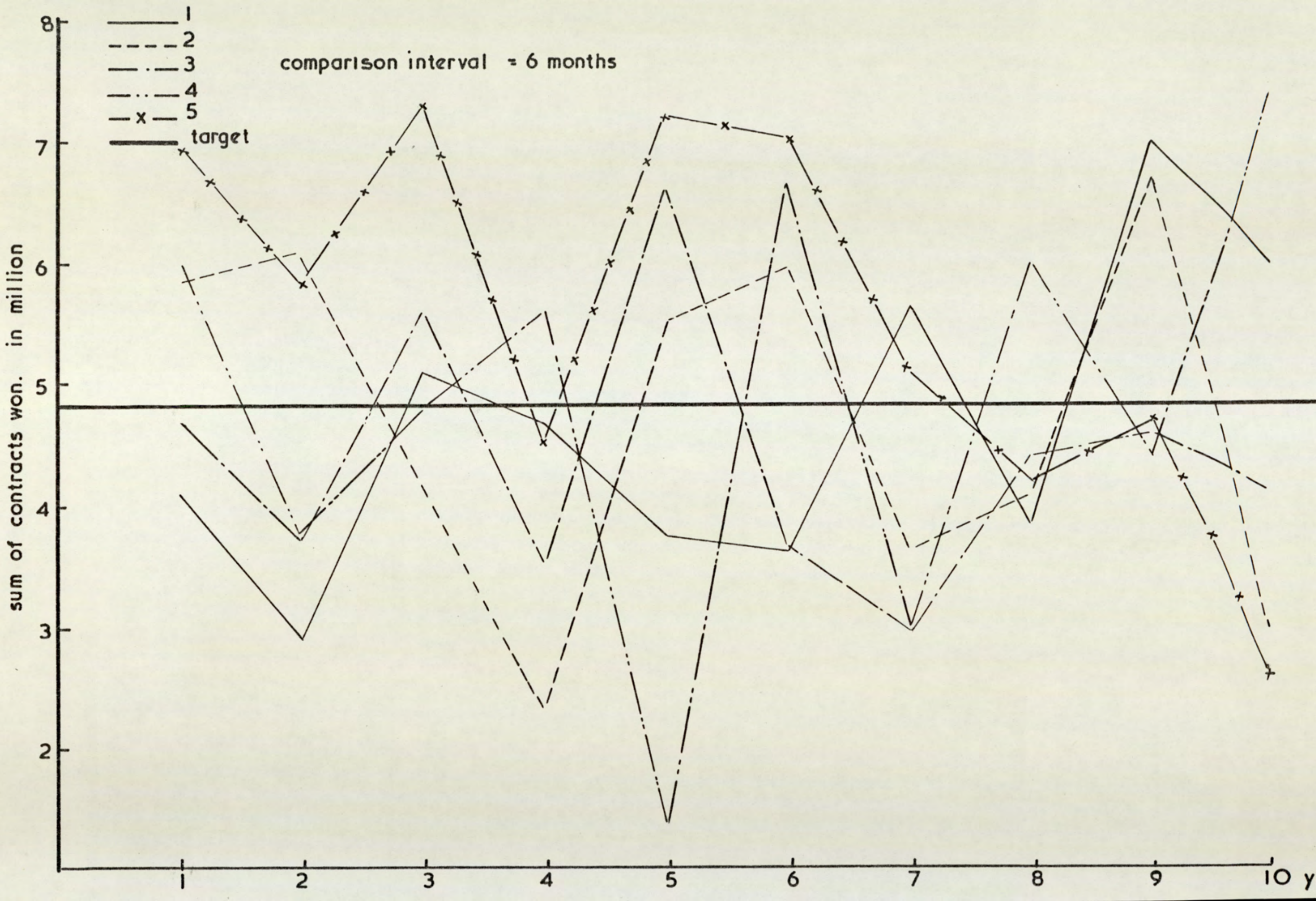

comparison interval = 6 months
1
2
3
4
5
target
sum of contracts won. in million
8
7
6
5
4
3
2
1
2
3
4
5
6
7
8
9
10 yr

Fig. 5.36

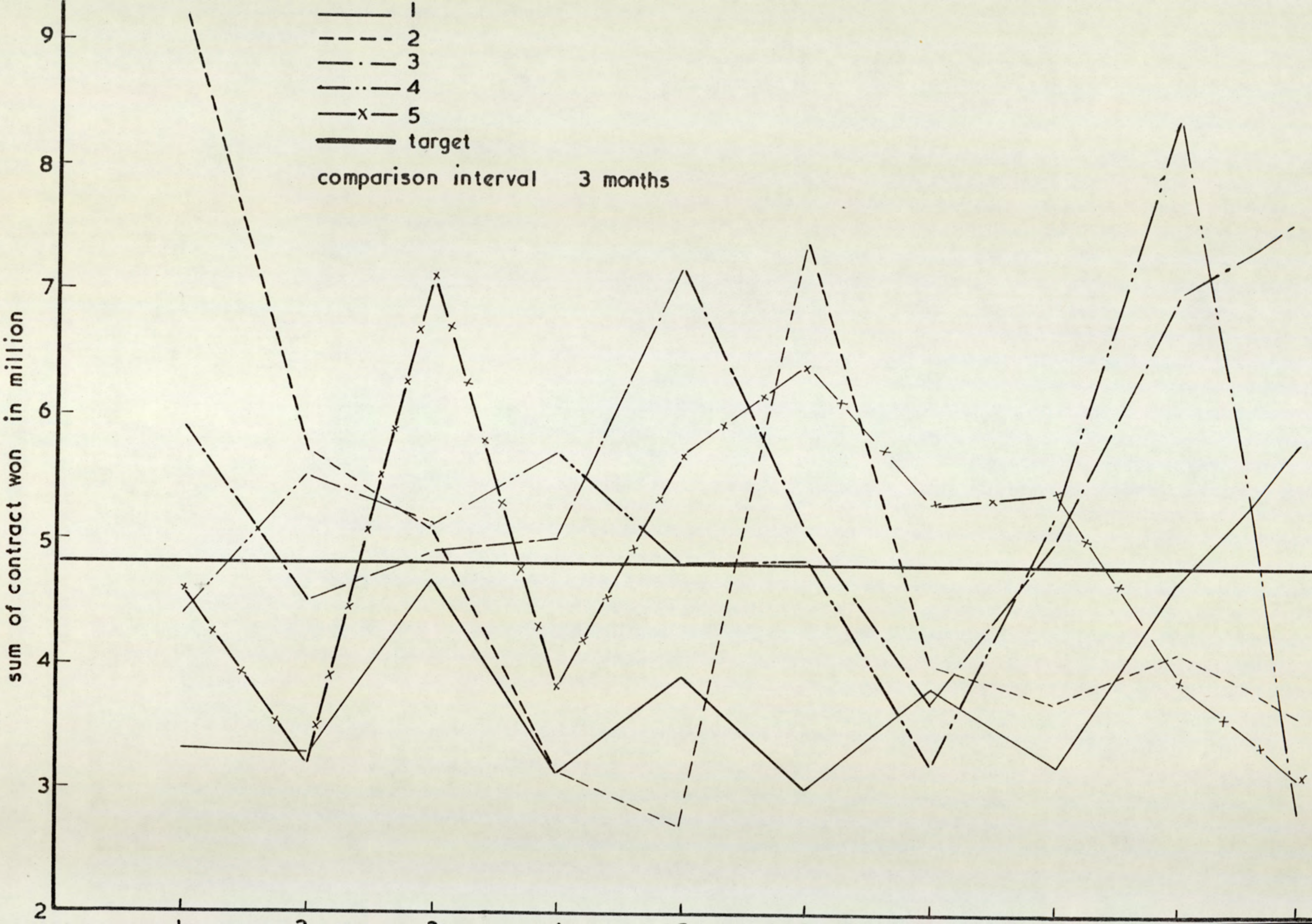
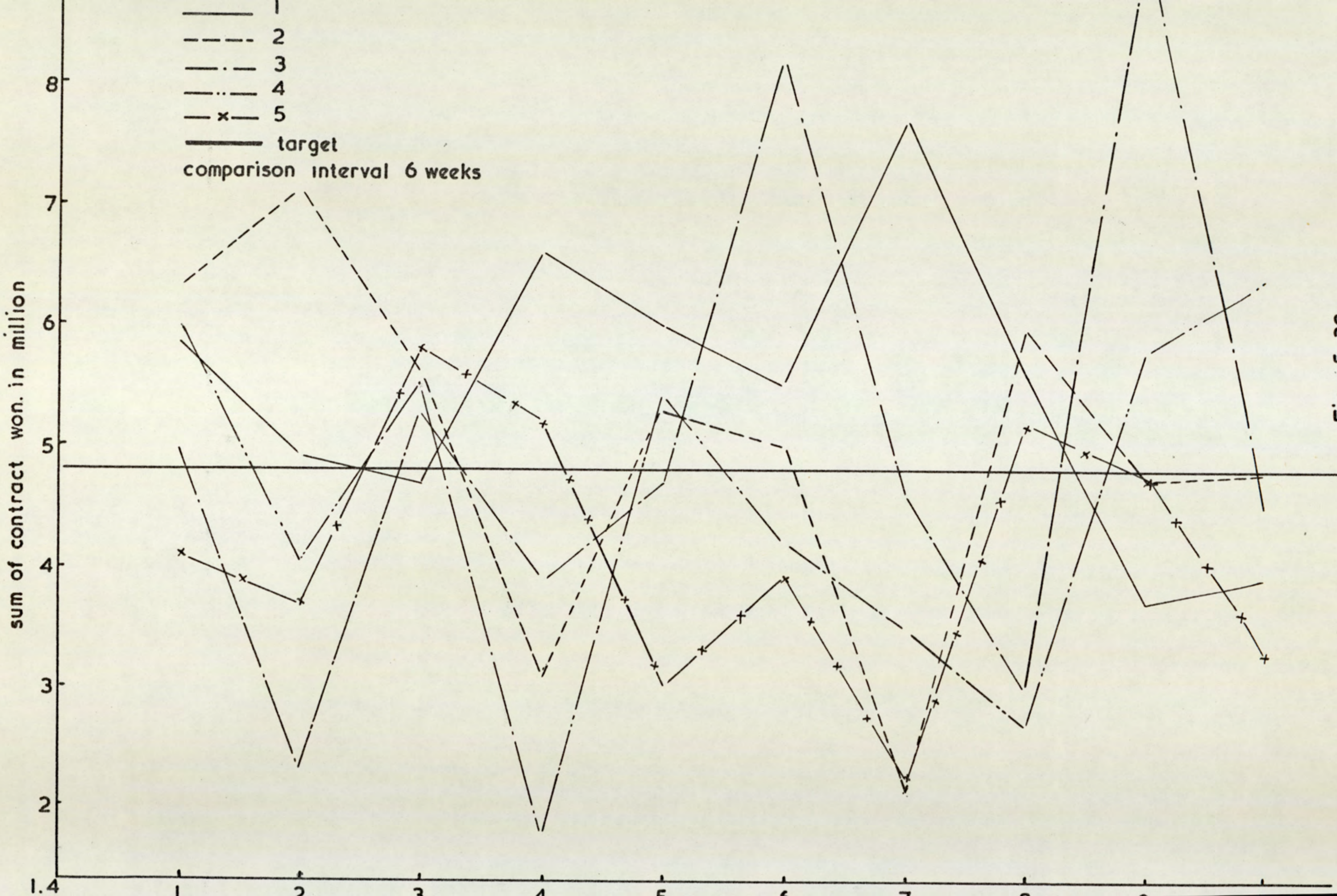
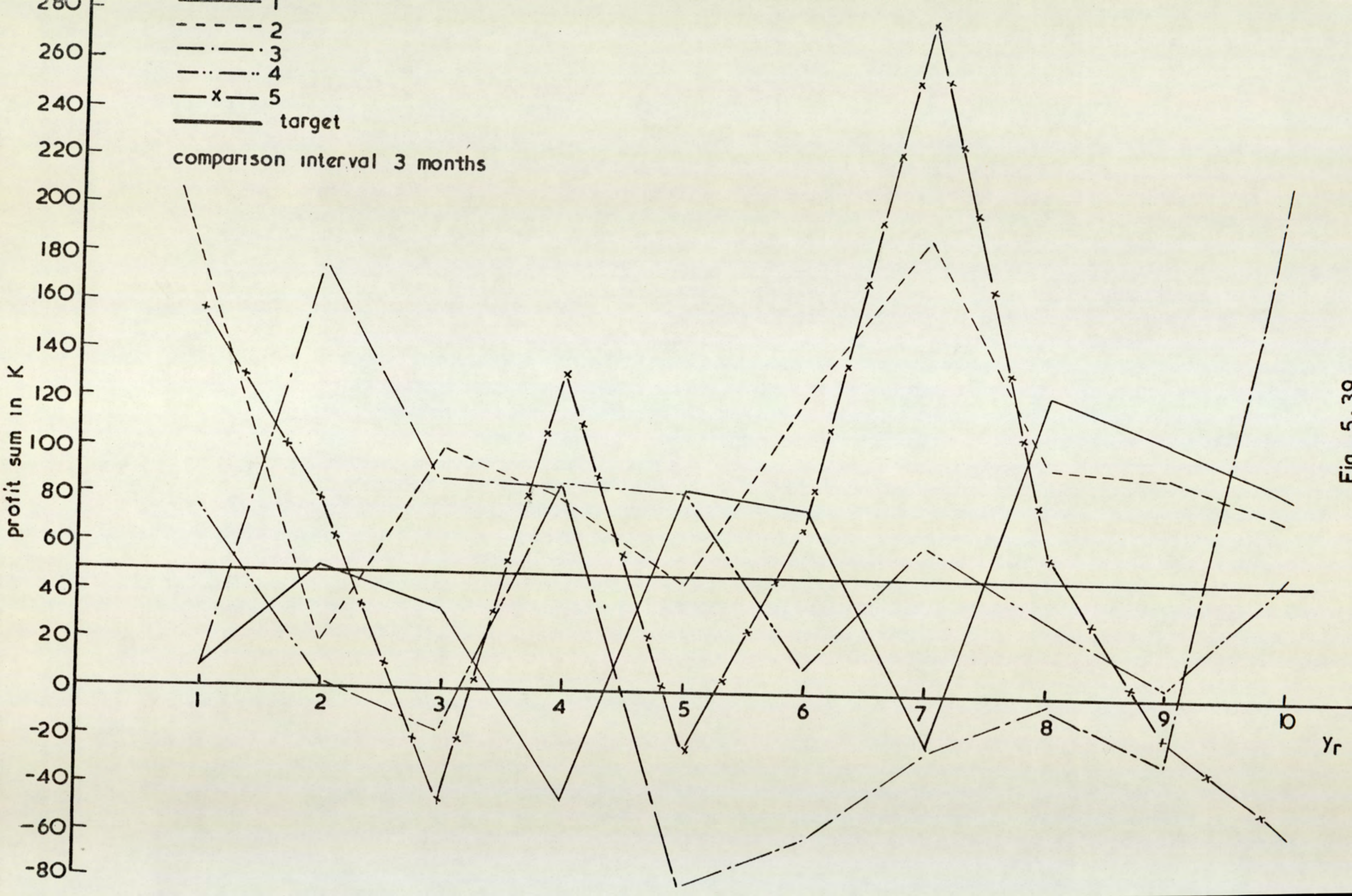

1
2
3
4
5
target
comparison interval 3 months
sum of contract won in million
9
8
7
6
5
4
3
2

Fig. 5.37



1
2
3
4
5
target
comparison interval 6 weeks
sum of contract won. in million
8
7
6
5
4
3
2
1.4

Fig. 5.38



1
2
3
4
5
target
comparison interval 3 months
profit sum in K
yr

Fig. 5.39

CHAPTER SIX

DISCUSSIONS AND CONCLUSIONS

6.1 Discussions:

The study of the various models and concepts of the theory of bidding strategy requires the analysis of a large volume of correct bidding data. Although two sets of data from two major contracting firms were available for this study, several attempts to obtain more sets resulted in failure due to the lack of cooperation from contractors who regard such information as a trade secret.

The goodness of fit of known statistical distributions to the data sets was tested and showed good agreement in some cases while no fit was found in others.

The relation between the number of competitors and the job value, which is a subject of disagreement between authors in the field of bidding strategy as discussed in Chapter 3, was investigated with the help of the two data sets. As each set indicated a different result, the study was inconclusive.

A study of the effect of job value on the coefficient of variation, the percentage spread, and the average standardised bid was conducted. The information available in the data sets indicated that the spreads of bids, in the high job value market is less than that in the low job value one, which is thought to be due to better estimation and similar mark-up policies in the high risk region.

The concept of expected utility value discussed in Chapter 2 was applied using one of the available data sets.

It is expected that the analysis of two data sets is not enough to draw firm conclusions especially in a field of controversy like that of bidding strategy. Even if more data sets are made available the reliability of their information remains in doubt as it is known that the contractor's site staff manipulate their reports to hide discrepancies. An example of this is sharing the time lost or money wasted on a certain item among several other items which were efficiently executed.

An alternative course of action which can be resorted to, is to assume known statistical distributions, of the elements involved in bidding strategy models, and draw samples from them using simulation techniques. The generation of random numbers is central to the application of simulation and the accuracy of the results depends on their true randomness.

The random numbers suitable for computerised simulation are pseudo random numbers for which two independant sources of generation were available. The first source is the Nottingham Algorithm Group Library routine available at the University's computer centre. This routine was tested and found satisfactory but its disadvantage is that it gives different random numbers every time it is called and a sequence cannot be regenerated for a later test. Although its cycle length is known, it is open for all users and it is not initiallized every time it is called. The second source of pseudo random number is a subroutine developed specially for this study which can be initiallized and hence reproduces the same sequence. This subroutine was successfully tested by various statistical methods and subsequently used in the simulation experiments.

The number of simulations required to arrive at a satisfactory accuracy was found by comparing the simulation results of selected problems to those obtained analytically by order statistics.

The concept of maximizing the expected profit was applied using computerised simulation. The effect of estimation accuracy was first investigated by fixing the number of competitors, the job value, and the mark-up of competitors M(THEM). The estimation accuracy was sampled from a uniform distribution and two curtailed normal distributions ($2\sigma =$ ER and $3\sigma =$ ER), and ER was taken as ±5%, ±10%, and ±15%. The results obtained by assuming a normal distribution of estimation accuracy, resulted in bids closer to the likely true cost than those obtained by assuming a uniform distribution.

The second investigation was concerned with the number of competitors. This number was varied between 1 and 10 and the effects on the success ratio, expected value, optimum mark-up, and optimum bid was studied. It was seen that the accurate estimation of the number of competitors is important when they are few and an error in this estimate of ±1 competitor has a great influence on the results. This accuracy becomes less important as the number of competitors increases and the difference in results between the cases of 9 and 10 competitors is very small.

The concept of the break even mark-up was tackled from a new angle taking into account the applied mark-up. In the special case of all contractors having the same mark-up, the results agree well with those published by other authors.

In a true bidding situation, the contractor's only control is over his mark-up, while the number of competitors and their mark-ups are uncontrolable by him. A study simulating this situation was conducted and the results were found to be dependent on the competitors mark-up range. When this range was from 0% to 10% a significant drop in the success ratio of the last contractor, whose mark-up is controlled, was compared with results obtained for various number of competitors with a fixed mark-up of 10%. However when the sampled mark-up range was changed to 5% - 15% so that its mean will correspond to the fixed mark-up case, the success ratio of the last contractor corresponded to that of the mean number of competitors with a fixed mark-up.

A simple decision theory analysis was conducted to the results obtained by sampling the competitors mark-ups between 5% - 15%. The decision model was assumed to be that of decision making under uncertainty and the various relevant criteria were applied.

An investigation to study the effect of the job value was also carried out. The job value was sampled from a uniform distribution whose limits are £50k and £1000k. Although no effect on the success ratio or average net profit was observed, the increase in overall profit was found to have a linear relation with the estimation accuracy.

Finally the concept of target probability was applied. It was seen that the mark-up can be used as a controlling factor of the work load.

Although a lot of important situations were simulated and the influence of several relevant factors was tested, there remains a great scope for further development and study. Some areas of possible further research are suggested in the following section.

6.2 Suggestions for further research

A) Verification of the computerised simulation results by comparisons with actual bidding data:

The confidence in the simulation results can be fully established when they compare well with actual bidding data. It is not certain, however, how such data can be made available but attempts must continue to do so.

B) The break even mark-up:

Previous studies of the BEMU neglected the effects of the mark-up and the job value. In this thesis these effects were included and they indicated that the results of the previous studies can be considered as a special case of a more general field. However, the mark-up of competitors M(THEM) was fixed at 10% which, in a true bidding situation, would be variable. This factor can be included in a simulation program which samples the competitors' mark-ups from various distributions with various limits and compare the results ideally with a contractor's set of data.

C) The number of competitors:

It was seen that some authors suggest a linear relation between the job value and the number of competitors while others suggest that it is non-linear. A third group are inconclusive about the existence of this relation. The results of this work are inconclusive also. Due to the importance of this factor, further attempts could be made to see if a relationship exists in a particular job value range or a special type of job. Factors, other than the job value, can be considered and their effect assessed to arrive at a model capable of predicting the number of competitors.

D) The estimation accuracy:

Of all the factors studied in this investigation, the estimation accuracy is the one which influenced the results most. A study of the job value indicated a possible relation with the estimation accuracy. The high job value bids had a lower spread indicating their being samples from a normal distribution while low job value bids, with their high spread, can be samples from a uniform distribution. The limits of the distribution can also be estimated.

E) Job availability:

In the simulation results the number of simulations, which represent the number of tenders bid for, was fixed at (500) which was found to be the number at which simulation results approach the theoretical ones. However, in a true bidding situation it is unlikely that a contractor has the opportunity to bid for 500 jobs per year and hence a study can be made to determine the optimum mark-up if the number of available jobs is fixed at a more realistic figure (say 20).

F) Development of a comprehensive simulation program:

A computer program can be developed incorporating the results of sections C and D. When selecting a job value range the number of competitors and the type of distribution and limits of the estimated accuracy are evaluated. Another factor which needs to be determined is the range of the competitors mark-up. The simulation experiment is conducted by varying M(US) and calculating the probability of winning and the average net profit associated with each one.

G) Further investigation of the concept of target probability:

The importance of this concept is that it does not aim at maximizing the profit but at maintaining a target volume of work for a contractor. The main factor in this concept is the time period after which the target value is compared to the amount of work obtained. The influence of the number of simulations, number of competitors, type and range of estimation accuracy, and the job value, on the time period, can be determined by conducting simulation experiments varying one or more of these factors and keeping the others as constants.

6.3 Conclusions

Two sets of bidding data were analysed and applied to some aspects of the field of bidding strategy. However, the results obtained from them cannot be generalized, as a general conclusion requires the analysis of a much larger volume of data.

As an alternative, computerised simulation was adopted and a pseudo random numbers generation subroutine was developed and tested. The subroutine was satisfactory and yielded good simulation accuracy with a relatively small number of simulations. The simulation results compare well with the theoretical published literature. The method can be developed further to examine other fields which were untackled in this thesis.

CHAPTER SEVEN

APPENDICES

7.1 The Computerised generation of Pseudo Random Numbers

7.1.1 Introduction

A ramdom sequence of numbers is a finite sequence in which each number has the same chance in appearing in any position in the sequence as any other number in the sequence.

There is no mathematical definition of a random sequence but it is possible to define the degree of randomness by subjecting the sequence to a number of statistical tests, [31].

There are several types of machines which generate random numbers, but the sequence produced by them cannot be regenerated which is clear from the definition of a random sequence. Due to this limitation, the testing or comparison of a sequence generated by this method is difficult. As an alternative, a Pseudo-Random-Number sequence may be generated by defining criteria for the sequence and then constructing a process that will satisfy the criteria, [31].

7.1.2 Generation of Pseudo-Random-Numbers (PRNs)

There are several methods for the generation of PRN's, but it must be noted that there is no method which produces perfect sets or is the best of all methods. It must also be noted that parts of a random sequence are not necessarily random but must be tested for local randomness, [32].

The method used in this thesis is the multiplicative congruential method which is described subsequently.

If two integers (a) and (b) differ by a multiple of a fixed natural number (m), it is said that (a) is "congruent" to (b) with respect to (m):

$$\text{i.e. } a = b \quad (\text{mod } m)$$

or

$$a = b \qquad (m)$$

This means that the difference between (a) and (b) must be divisible by (m) so that:

$$\frac{(a - b)}{m} = d$$

where (d) is an integer.

This suggests a method for the generation of PRN by:

$$R_m = k\ R_{m-1} \mod b^n.$$

where

R_m = m^{th} random number generated from the m-1 random number.

k = multiplier

and the length of the cycle is given by b^{n-2}.

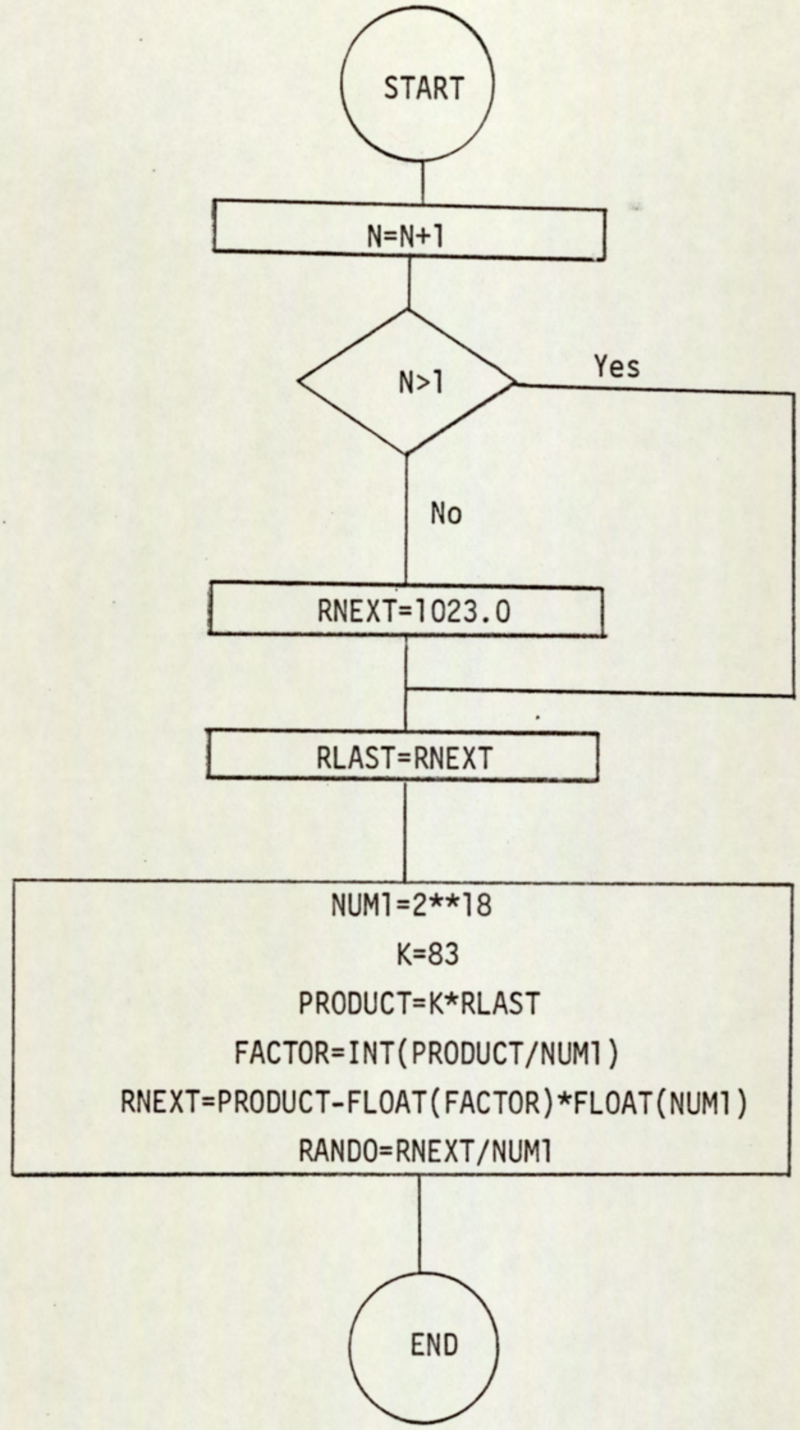
This method will produce integers, so if random fractions are required, the result is divided by b^n. The properties of the sequence were found to be insensitive to m, [3], therefore the length of the cycle can be determined by the computer characteristics. For a computer with a word length of b bits, the value of m can be chosen as $m = 2^b$. The power of 2 is used to increase the speed of the machine as it will reduce the division to an operation of arithmetic shift. However, this may be true if lower level languages are used, but there is no advantage in it when using a high level language like Fortran. To make the best of the word length of the computer, the product of integers is evaluated in floating point form using the (FLOAT) statement so that each value involved in the multiplication process can have the maximum size allowed by the computer.

For a binary computer the following parameters are recommended, [3].

R_{m-1} = any integer

$k = 8t \pm 3$ where t is any integer, whose value was chosen as 10 in this work.

Following is the flow chart of subroutine RANDY:


START
N=N+1
N>1
Yes
No
RNEXT=1023.0
RLAST=RNEXT
NUM1=2**18
K=83
PRODUCT=K*RLAST
FACTOR=INT(PRODUCT/NUM1)
RNEXT=PRODUCT-FLOAT(FACTOR)*FLOAT(NUM1)
RANDO=RNEXT/NUM1
END

7.1.3 NAG routine for PRNs generation

The University Computer Centre has a standard routine for generating PRN's from Nottingham Algorithm Group Library. It was not possible to determine details of the technique used in this routine. This routine was used together with the one developed in this thesis in simulation problems where PRN's from two independent streams are required.

7.1.4 Statistical tests

The NAG routine and RANDY were used to sample from a uniform distribution of estimating accuracy (± 10%) using 5 bidders and a 10% mark up on estimated cost. The exact average net profit on bids won is 2.67%. The simulated results for 500 simulations were as follows:

NAG ROUTINE	2.684% (av. net profit)
RANDY	2.686% (av. net profit)

Although both generators appear to be reasonably efficient it was; decided to apply two statistical tests of randomness namely the frequency and serial tests.

i) Frequency test:

The properties of the sequence generated were

$$k = 83$$
$$R_1 = 1023$$
$$m = 2^{18}$$

This test is carried out to ensure that the PRNs generated by the sequence in every subsection differ from the expected number by an acceptable amount, [33]. The range between 0 and 1 was divided into ten equal subsections (0.0 to 0.1, 0.1 to 0.2..etc.). A computer program was written to sum the PRNs in each sub group from a sequence of 500 PRNs, and taking the expected frequency at each sub-section as 500/10=50 the resultswhich are presented in Table (7.1) show that:

$$\chi^2 = \sum_{i=1}^{10} (e_i - 0_i)^2/e_i = 12.04$$

The value of χ^2 at a 5% level of significance and 9 degrees of freedom is $\chi^2 = 16.919$.

As $16.919 > 12.04$ therefore the sequence is random for this level of significance.

The parameters of the sequence were changed to:

$$k = 83$$

$$R = 255$$

$$m = 2^{14}$$

and the same test was applied. The result was

$$\chi^2 = 9.12$$

As $16.919 > 9.12$ therefore the new sequence is random for this level of significance also.

TABLE (7.1)

Observed freq. (0)	Expected freq. (e)	e - 0	$(e - 0)^2$	$\frac{(e - 0)^2}{e}$
54.0	50.0	-4.0	16.0	0.320
65.0	50.0	-15.0	225.0	4.50
51.0	50.0	-1.0	1.0	0.02
52.0	50.0	-2.0	4.0	0.08
36.0	50.0	14.0	196.0	3.92
45.0	50.0	5.0	25.0	0.50
44.0	50.0	6.0	36.0	0.72
59.0	50.0	-9.0	81.0	1.62
47.0	50.0	3.0	9.0	0.18
47.0	50.0	3.0	9.0	0.18
Σ 500.0	500			12.04

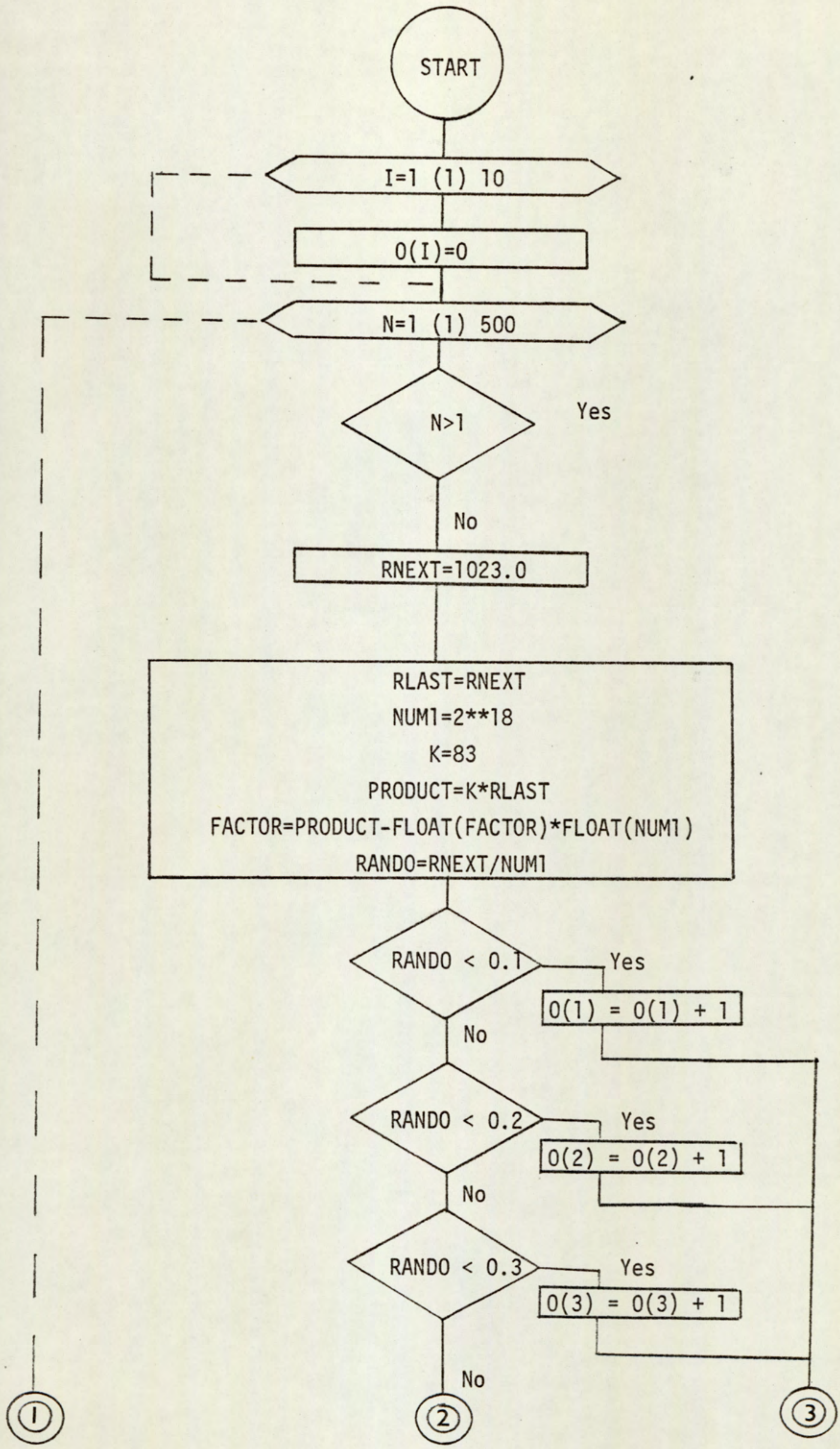
The NAG library routine was subjected to the same test and the result was:

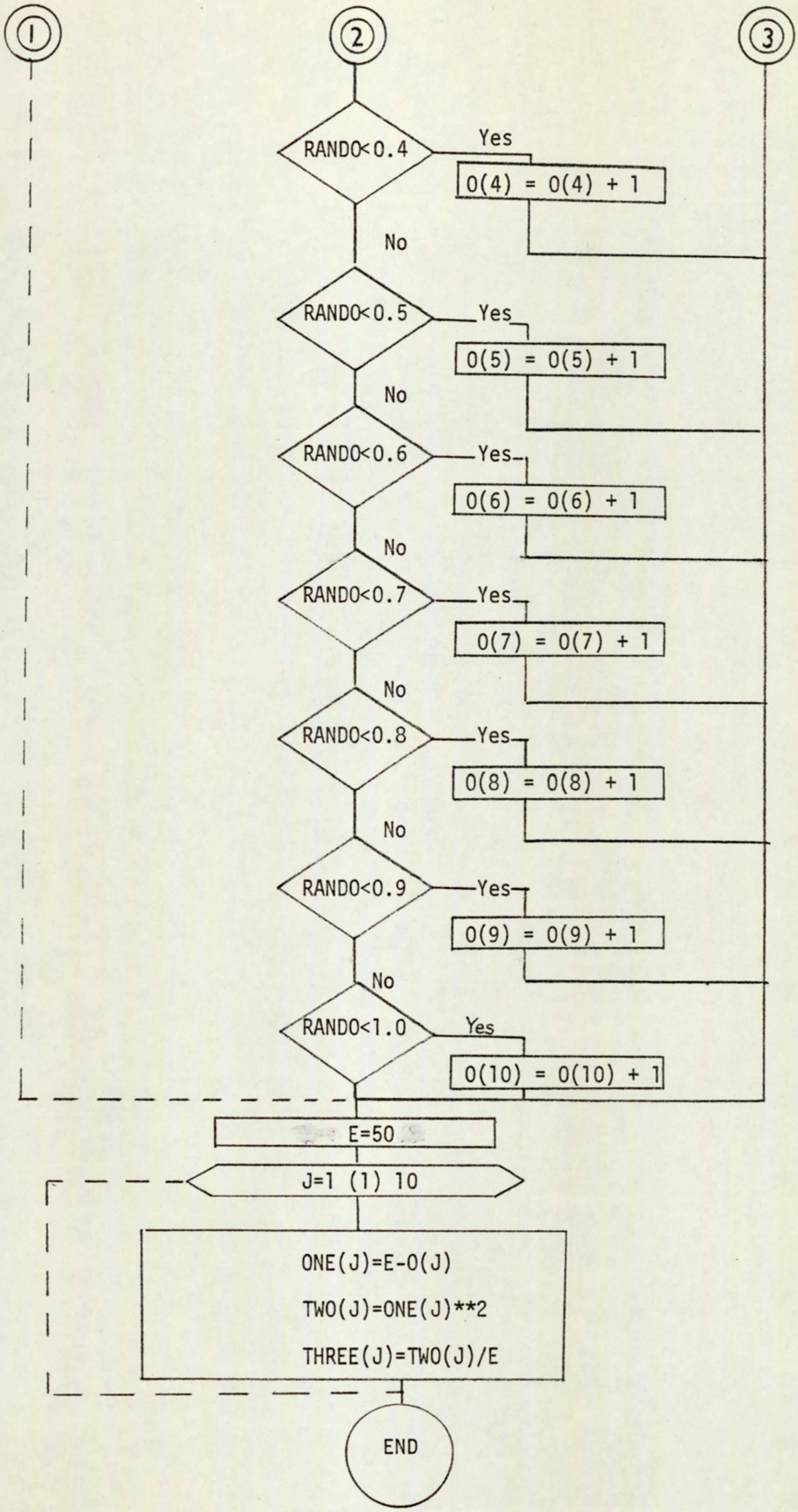
$$\chi^2 = 2.88$$

As $16.919 > 2.88$ therefore the NAG library routine satisfies this test.

The results for the sequence with parameters $k = 83$, $R = 1023$, and $m = 2^{18}$ and the NAG library routine are shown in Fig. 7.1

Following is the flow chart of the computer program used in this test:


START
I=1 (1) 10
0(I)=0
N=1 (1) 500
N>1
Yes
No
RNEXT=1023.0
RLAST=RNEXT
NUM1=2**18
K=83
PRODUCT=K*RLAST
FACTOR=PRODUCT-FLOAT(FACTOR)*FLOAT(NUM1)
RANDO=RNEXT/NUM1
RANDO < 0.1
Yes
0(1) = 0(1) + 1
No
RANDO < 0.2
Yes
0(2) = 0(2) + 1
No
RANDO < 0.3
Yes
0(3) = 0(3) + 1
No
1
2
3


1
2
3
RANDO<0.4
Yes
O(4) = O(4) + 1
No
RANDO<0.5
Yes
O(5) = O(5) + 1
No
RANDO<0.6
Yes
O(6) = O(6) + 1
No
RANDO<0.7
Yes
O(7) = O(7) + 1
No
RANDO<0.8
Yes
O(8) = O(8) + 1
No
RANDO<0.9
Yes
O(9) = O(9) + 1
No
RANDO<1.0
Yes
O(10) = O(10) + 1
E=50
J=1 (1) 10
ONE(J)=E-O(J)
TWO(J)=ONE(J)**2
THREE(J)=TWO(J)/E
END

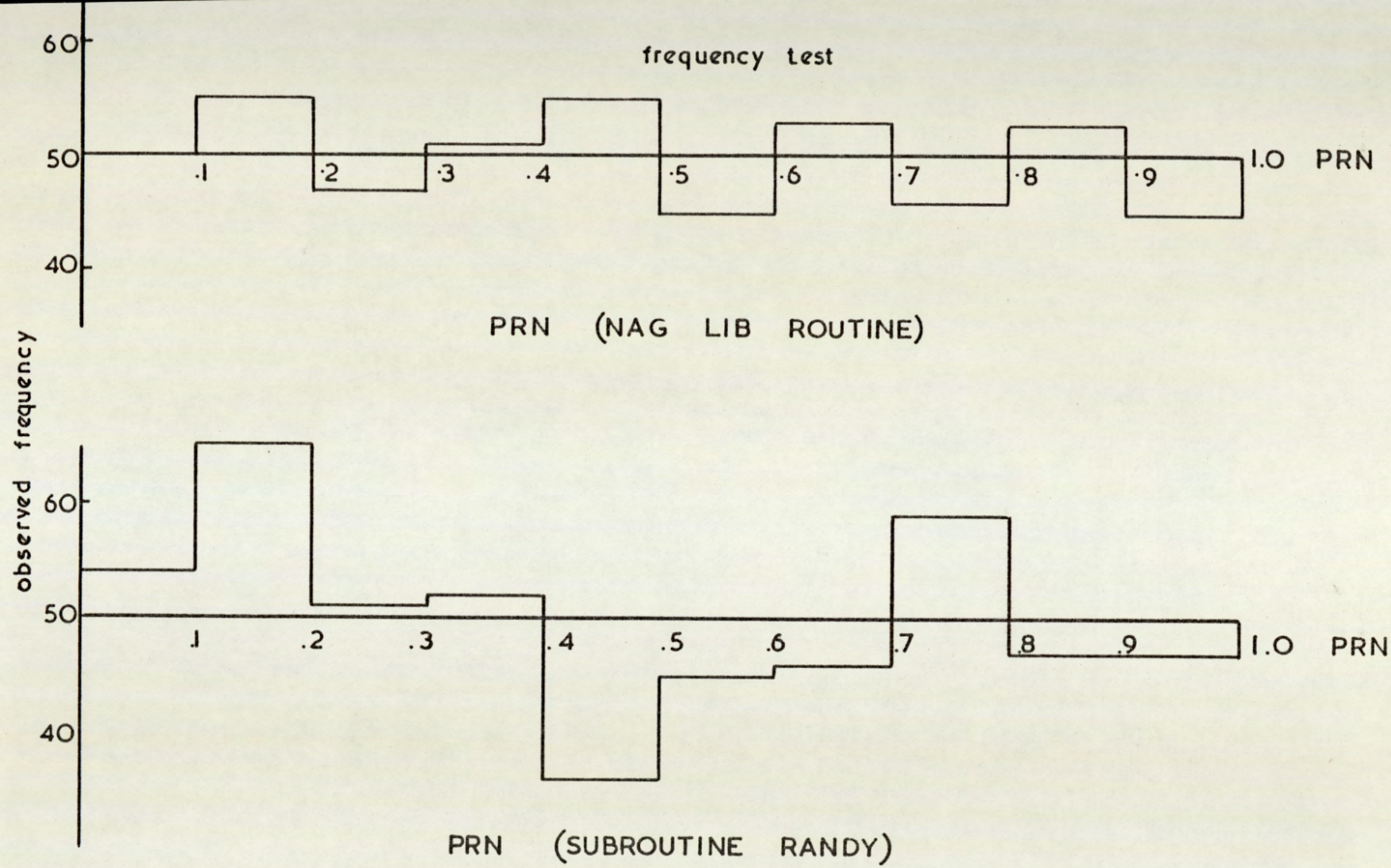

frequency test
observed frequency
60
50
40
.1 .2 .3 .4 .5 .6 .7 .8 .9 1.0 PRN
PRN (NAG LIB ROUTINE)
60
50
40
.1 .2 .3 .4 .5 .6 .7 .8 .9 1.0 PRN
PRN (SUBROUTINE RANDY)

Fig . 7.1.

ii) Serial test:

This test studies the relation between each two consecutive numbers in the sequence and records how many times a number between 0 and 9 follow the number 0, similarly (1), (2).....(9), [33]. By constructing a matrix of 10 x 10 the sum of the rows and columns must be equal. The results are shown in Table (7.2).

It is seen that the total of the i^{th} row and column are equal.

Since there are 10 linear constraints, imposed by the condition that the total of corresponding rows and columns are equal, the number of degreesof freedom is 90:

It has been shown that

$$S^2 = \sum_{i=1}^{100} \frac{(e_i - 0_i)^2}{e_i} - \sum_{i=1}^{10} \frac{(\bar{e}_i - \bar{0}_i)}{\bar{e}_i}$$

where

e_i = expected frequency in each cell

0_i = observed frequency in each cell

$\bar{e}_i$ = expected column or row total

$\bar{0}_i$ = observed column or row total

$$\sum_{i=1}^{100} \frac{(e_i - 0_i)^2}{e_i} = 122.2$$

$$\sum_{i=1}^{10} \frac{(\bar{e}_i - \bar{0}_i)^2}{\bar{e}_i} = 11.54$$

$$S^2 = 122.2 - 11.54 = 110.66$$

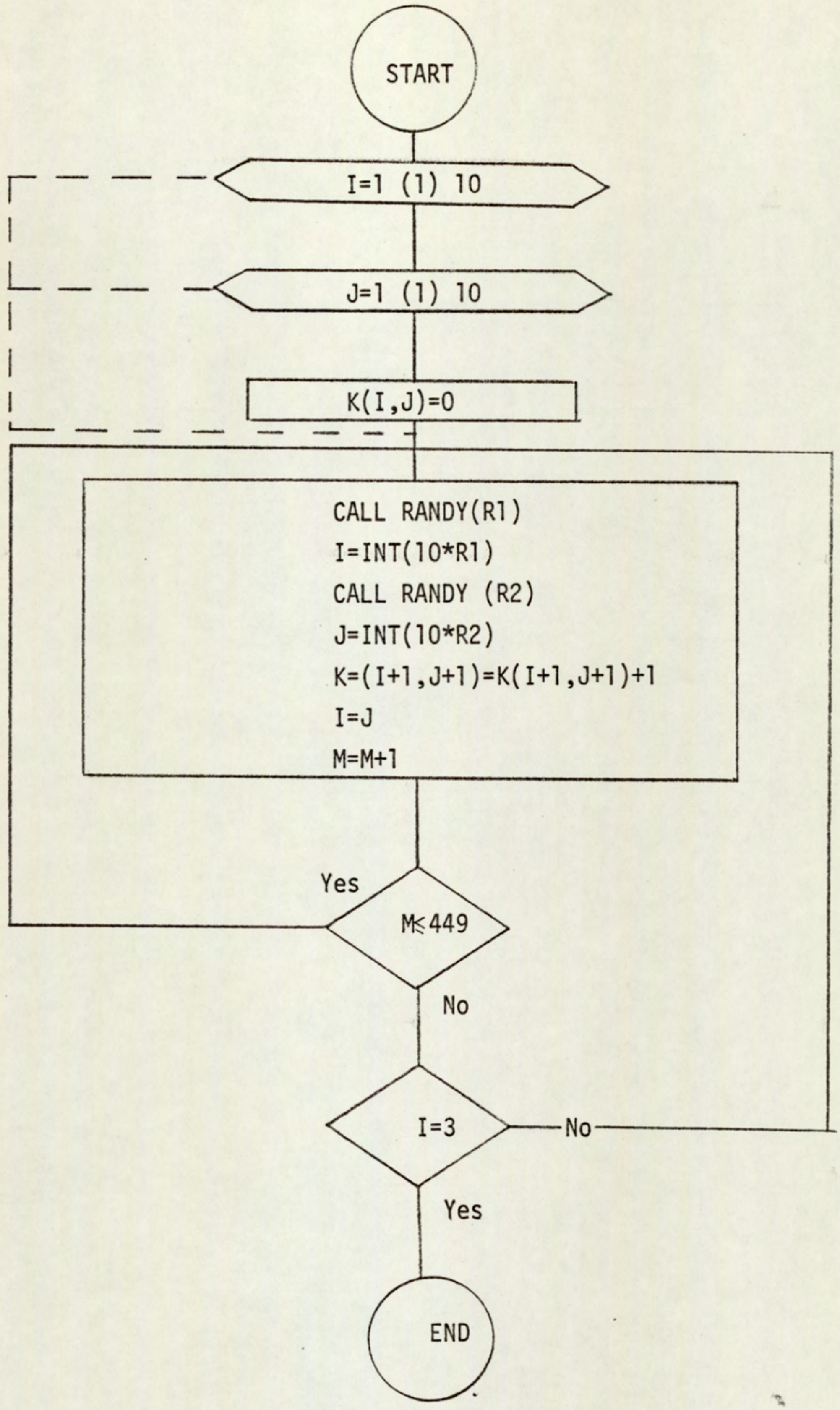
TABLE (7.2)

	0	1	2	3	4	5	6	7	8	9	T
0	12	8	4	3	4	5	3	10	2	3	54
1	6	10	8	6	4	7	5	5	8	6	65
2	5	7	1	5	2	3	8	8	7	5	51
3	7	4	2	8	6	4	1	7	6	7	52
4	3	3	3	5	3	2	4	5	5	3	36
5	6	9	9	4	1	7	2	1	3	3	45
6	2	3	5	5	6	6	5	3	5	6	46
7	5	4	4	6	7	4	7	8	8	6	59
8	5	7	12	1	2	3	7	5	1	5	48
9	3	10	3	9	1	4	4	7	3	3	47
T	54	65	51	52	36	45	46	59	48	47	503

The value of χ^2 at a 5% level of significance and 90 degrees of freedom is $\chi^2 = 113.1$.

As 113.1 > 110.66 therefore the sequence is random for that level of significance.

Following is the flow chart of the computer program used in this test:


START
I=1 (1) 10
J=1 (1) 10
K(I,J)=0
CALL RANDY(R1)
I=INT(10*R1)
CALL RANDY (R2)
J=INT(10*R2)
K=(I+1,J+1)=K(I+1,J+1)+1
I=J
M=M+1
Yes
M≤449
No
I=3
No
Yes
END

7.2 Computer programs flow charts

7.2.1 Introduction

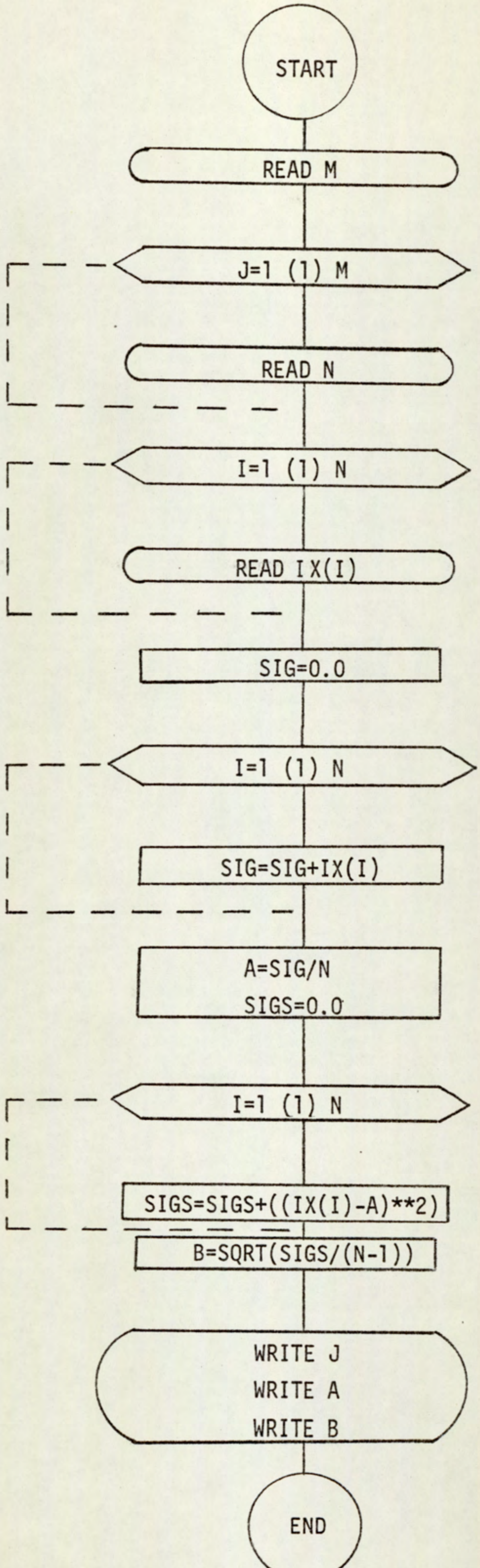
The simulation experiments carried out can be divided into two groups, namely the ones with a fixed job value and the ones with a variable job value. The other computerised simulation carried out was to apply the concept of target probability. For the fixed job value programs the estimation accuracy distribution was assumed to be uniform, normal where $3\sigma = \pm ER\%$, and normal where $2\sigma = \pm ER\%$. In all three cases the master segment is the same and the only difference is in subroutine (LEBIDDER), therefore the master segment flow chart will be described once only. The concept of target probability was applied with a uniformly distributed estimation accuracy only. In all programs subroutine RANDY is used but its flow chart will not be included here as it was described in the previous section.

7.2.2 The program to evaluate the mean and standard deviation

This program evaluates the mean and standard deviation of sets of bids for a given number of contracts. The steps performed are as follows:

1) The number of contracts are read and a loop around it is constructed.
2) The number of bids for the first contract are read.
3) The values of the bids are accumulated and divided by their number to give the mean.
4) The standard deviation is calculated.
5) The results of step 3 and step 4 are outputed.
6) The procedure is repeated from step 2 for the subsequent contracts.

Following is the program flow chart:


START
READ M
J=1 (1) M
READ N
I=1 (1) N
READ IX(I)
SIG=0.0
I=1 (1) N
SIG=SIG+IX(I)
A=SIG/N
SIGS=0.0
I=1 (1) N
SIGS=SIGS+((IX(I)-A)**2)
B=SQRT(SIGS/(N-1))
WRITE J
WRITE A
WRITE B
END

```
      TRACE 1
      MASTER MASTD
      REAL IX(50)
      READ(1,1)M
      DO9 J=1,M
      READ(1,1)N
      DO2 I=1,N
2     READ(1,3) IX(I)
      SIG=0.0
      DO4 I=1,N
4     SIG=SIG+IX(I)
      A=SIG/N
      SIGS=0.0
      DO 5 I=1,N
5     SIGS=SIGS+((IX(I)-A)**2)

      D=SQRT(SIGS/(N-1))
      C=(D/A)*100
 9    CONTINUE
 1    FORMAT(I2)
3     FORMAT(F8.0)
      STOP
      END
```

7.2.3 Programs for simulations with a fixed job value

A) Uniformly distributed estimation accuracy:

The steps carried out in the master segment are as follows:

1) The number of jobs with different parameters are read.

2) The number of simulations and the number of competitors are read.

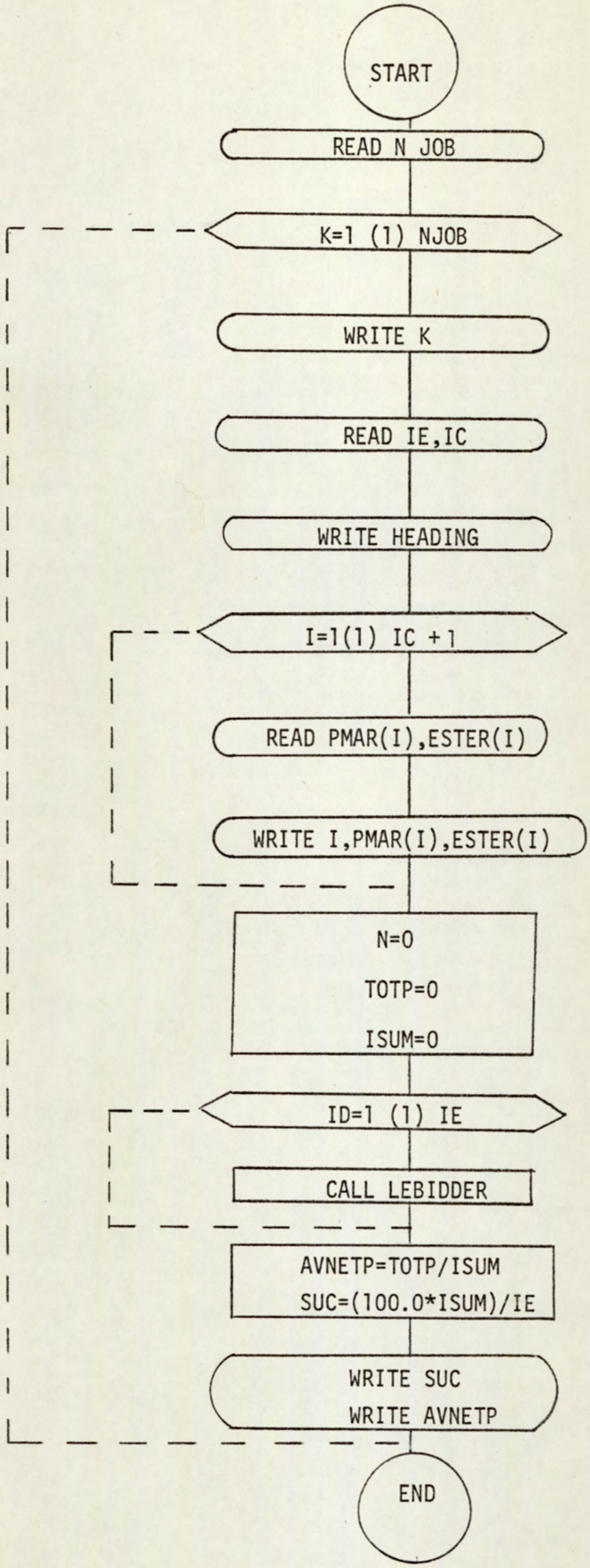
3) The profit margin and estimation accuracy of each contractor are read.

4) The total profit and the number of contracts won are initialized.

5) Subroutine LEBIDDER is called to find the winner in each simulation.

6) The success ratio and the average net profit of the last contractor are evaluated and outputed.

Following is the flow chart of the master segment:


START
READ N JOB
K=1 (1) NJOB
WRITE K
READ IE,IC
WRITE HEADING
I=1(1) IC +1
READ PMAR(I),ESTER(I)
WRITE I,PMAR(I),ESTER(I)
N=0
TOTP=0
ISUM=0
ID=1 (1) IE
CALL LEBIDDER
AVNETP=TOTP/ISUM
SUC=(100.0*ISUM)/IE
WRITE SUC
WRITE AVNETP
END

Subroutine LEBIDDER finds the winner in each simulation, and if it is the last contractor then it accumulates his profit and number of won contracts. The steps carried out are as follows:

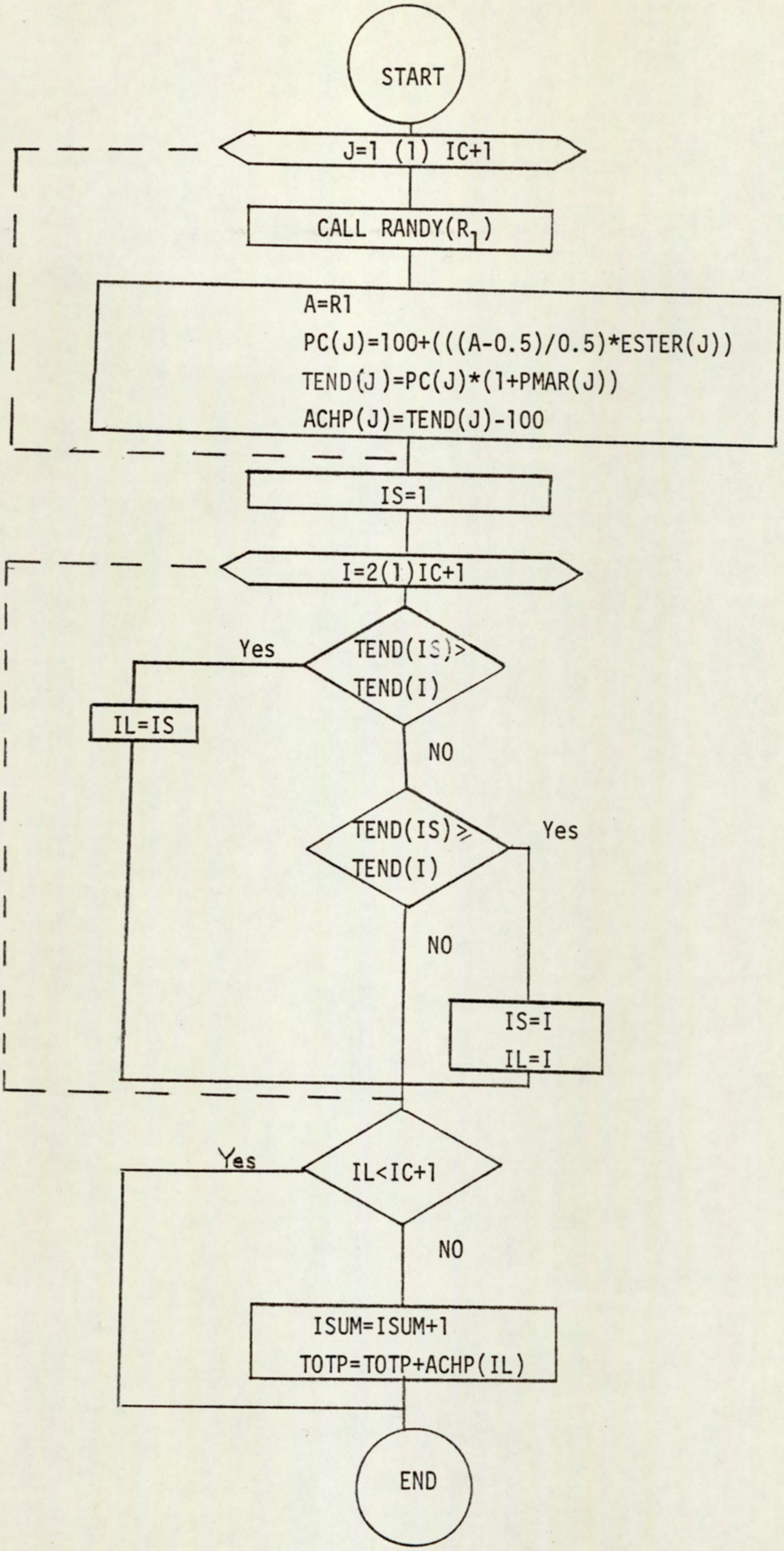
1) Subroutine RANDY is called to generate a random number which will be used in sampling a value for the estimation accuracy from a uniform distribution for each contractor.

2) The prime cost, tender value, and achieved profit for each contractor are evaluated.

3) The tender values are compared to find the winner (which is the lowest).

4) If the winner is the last contractor then his achieved profit and number of contracts won are accumulated and stored.

Following is the flow chart of the subroutine.


START
J=1 (1) IC+1
CALL RANDY(R1)
A=R1
PC(J)=100+(((A-0.5)/0.5)*ESTER(J))
TEND(J)=PC(J)*(1+PMAR(J))
ACHP(J)=TEND(J)-100
IS=1
I=2(1)IC+1
TEND(IS)> TEND(I)
Yes
IL=IS
NO
TEND(IS)≥ TEND(I)
Yes
NO
IS=I
IL=I
IL<IC+1
Yes
NO
ISUM=ISUM+1
TOTP=TOTP+ACHP(IL)
END

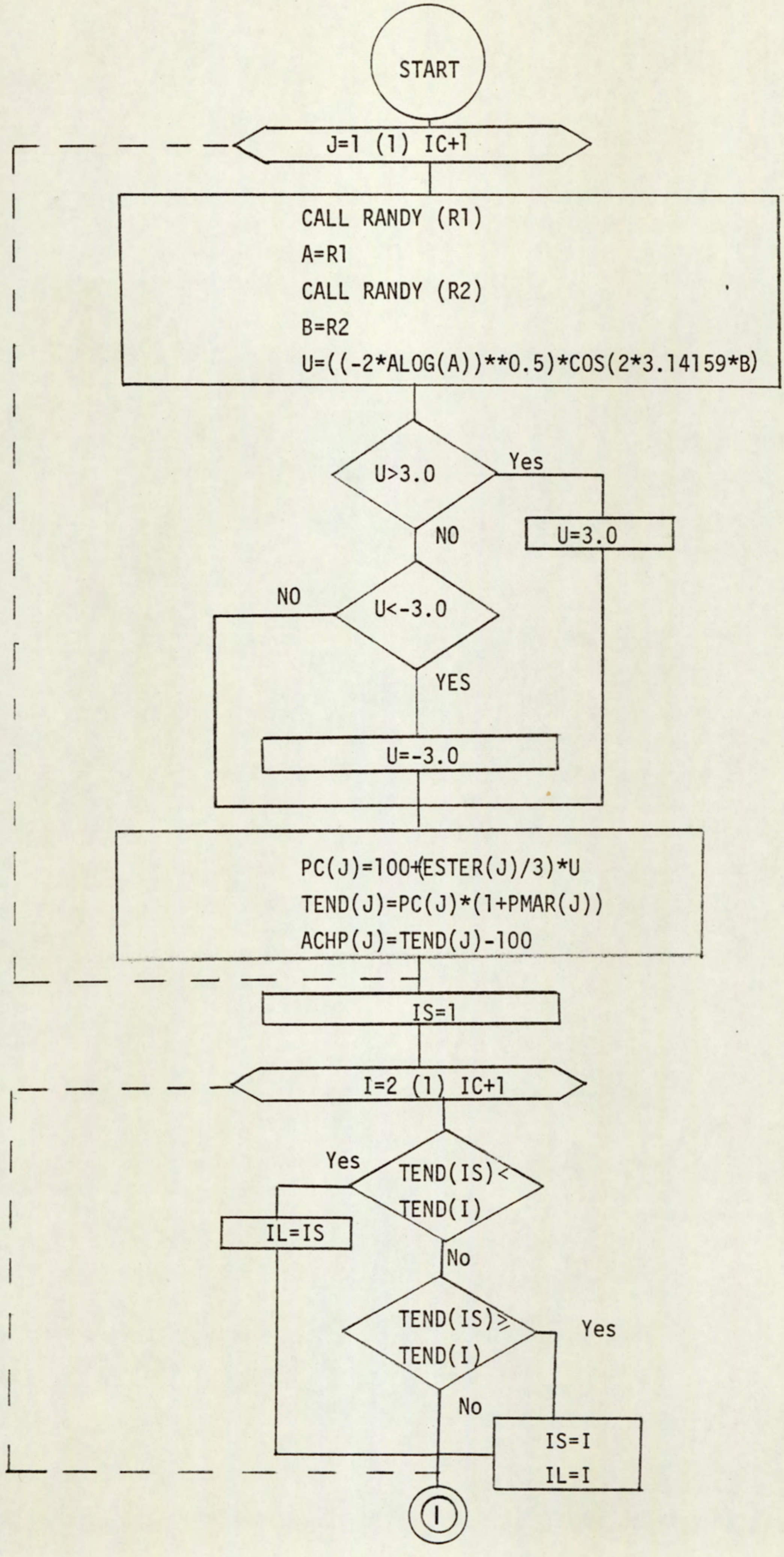
```
      MASTER ALI
      DIMENSION PMAR(50),ESTER(50)
      COMMON N,IC,PMAR,ISUM,TOTP,ESTER
      READ(1,17)NJOB
C NJOB=NO OF JOBS EACH WITH DIFF PARAMETERS
      DO 18 K=1,NJOB
      WRITE(2,19)K
      READ (1,5)IE,IC
C IE=NO OF COMPARED CONTRACTS
C IC=NO OF COMPETITORS PER CONTRACT
      WRITE(2,25)
      DO 14 I=1,IC+1
      READ(1,15)PMAR(I),ESTER(I)
   14 WRITE(2,13)I,PMAR(I),ESTER(I)
C PMAR=PROFIT MARGIN
C ESTER=ESTIMATION ERROR
   15 FORMAT(F10.3,F10.3)
      N=0
      TOTP=0
      ISUM=0
      DO 3 ID=1,IE
      EXTERNAL RANDY
      CALL LEBIDDER(RANDY)
    3 CONTINUE
C ISUM=NO OF BIDS WON BY E IN NO OF COMPARED CONTRACTS
C TOTP=E TOTAL PROFIT FOR ALL WON CONTRACTS
C AVNETP=E AVERAGE NET PROFIT PER WON CONTRACT
      AVNETP=TOTP/ISUM
C SUC=E PERCENTAGE SUCCESS IN NO OF COMPARED CONTRACTS
      SUC=(100.0*ISUM)/IE
      WRITE(2,9) SUC
      WRITE(2,16)AVNETP
    5 FORMAT(I7,I7)
    9 FORMAT(20H ESUCCESS PERCENT = ,F10.3,/)
   13 FORMAT(I7,F10.3,F10.3)
   16 FORMAT(22H AVERAGE NET PROFIT = ,F10.3,//)
   17 FORMAT(I7)
   19 FORMAT(14H JOB NUMBER : ,I7,/)
   25 FORMAT(29H  BIDDER    PROFMAR  ESTERROR)
   18 CONTINUE
      STOP
      END
      SUBROUTINE RANDY(RANDO)
      COMMON N,IC,PMAR,ISUM,TOTP,ESTER
      INTEGER FACTOR
      N=N+1
      IF(N.GT.1) GOTO 10
      RNEXT=1023.0
   10 RLAST=RNEXT
```

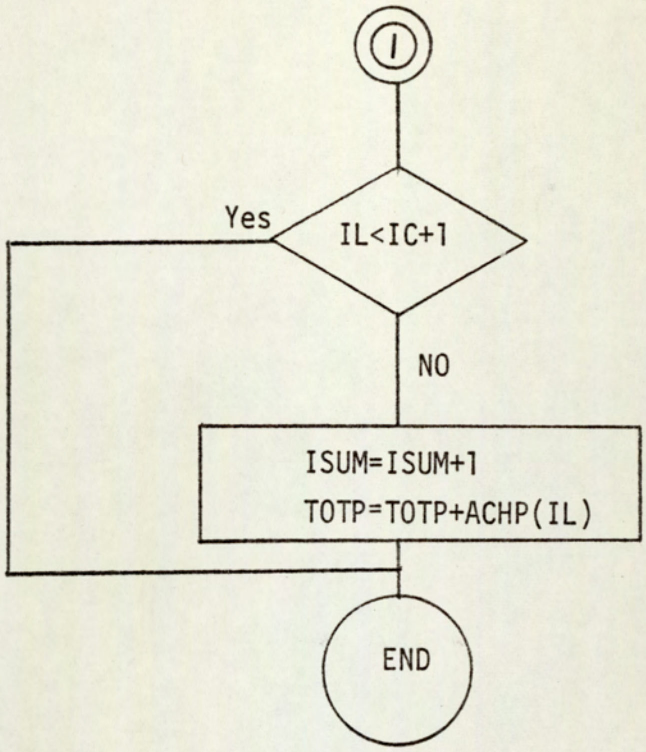
```
      NUM1=2**18
      K=83
      PRODUCT=K*RLAST
      FACTOR=INT(PRODUCT/NUM1)
      RNEXT=PRODUCT-FLOAT(FACTOR)*FLOAT(NUM1)
      RANDO=RNEXT/NUM1
      RETURN
      END
      SUBROUTINE LEBIDDER(RANDY)
      DIMENSION PC(50),TEND(50),ACHP(50),ESTER(50),PMAR(50)
      COMMON N,IC,PMAR,ISUM,TOTP,ESTER
      DO 12 J=1,IC+1
  2   CALL RANDY(R1)
      A=R1
      PC(J)=100*(((A-0.5)/0.5)*ESTER(J))
      TEND(J)=PC(J)*(1+PMAR(J))
      ACHP(J)=TEND(J)-100
 12   CONTINUE
 31   IS=1
      DO 20 I=2,IC+1
      IF(TEND(IS)-TEND(I))21,22,22
 21   IL=IS
      GO TO 20
 22   IS=I
      IL=I
 20   CONTINUE
      IF(IL.LT.IC+1)GOTO 11
      ISUM=ISUM+1
      TOTP=TOTP+ACHP(IL)
 11   CONTINUE
      RETURN
      END
      FINISH
```

B) Normally distributed estimation accuracy $3\sigma = \pm ER\%$.

The only difference in this case is that the PRNs generated are used for sampling from a normal distribution with $3\sigma = \pm ER\%$ as described in section (5.2).

Following is the flow chart of subroutine LEIBIDDER:


START
J=1 (1) IC+1
CALL RANDY (R1)
A=R1
CALL RANDY (R2)
B=R2
U=((-2*ALOG(A))**0.5)*COS(2*3.14159*B)
U>3.0
Yes
NO
U=3.0
NO
U<-3.0
YES
U=-3.0
PC(J)=100+(ESTER(J)/3)*U
TEND(J)=PC(J)*(1+PMAR(J))
ACHP(J)=TEND(J)-100
IS=1
I=2 (1) IC+1
Yes
TEND(IS)<
TEND(I)
IL=IS
No
TEND(IS)≥
TEND(I)
Yes
No
IS=I
IL=I
1


1
Yes
IL<IC+1
NO
ISUM=ISUM+1
TOTP=TOTP+ACHP(IL)
END

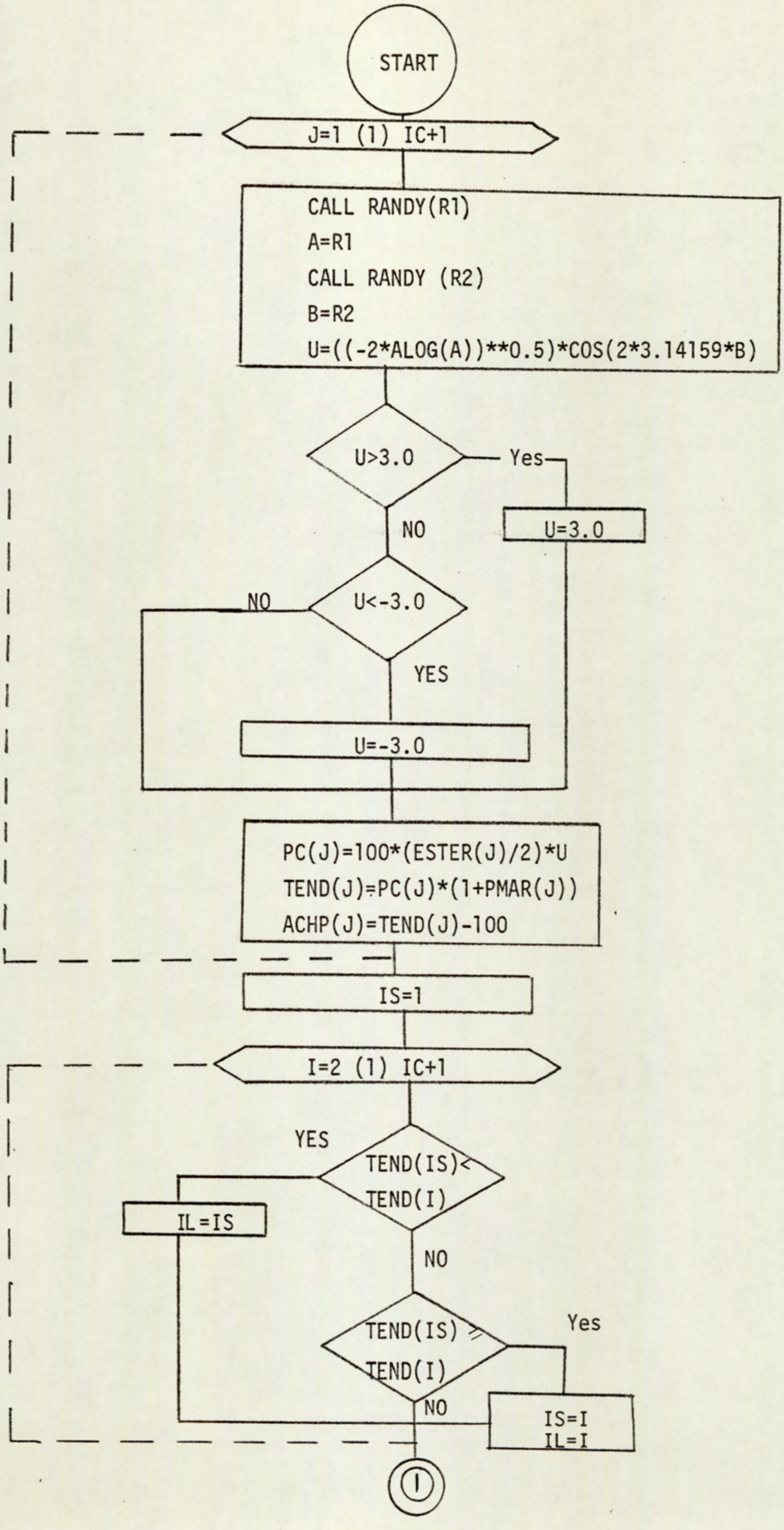
```
      MASTER ALI
      DIMENSION PMAR(50),ESTER(50)
      COMMON N,IC,PMAR,ISUM,TOTP,ESTER
      READ(1,17)NJOB
C NJOB=NO OF JOBS EACH WITH DIFF PARAMETERS
      DO 18 K=1,NJOB
      WRITE(2,19)K
      READ (1,5)IE,IC
C IE=NO OF COMPARED CONTRACTS
C IC=NO OF COMPETITORS PER CONTRACT
      WRITE(2,25)
      DO 14 I=1,IC+1
      READ(1,15)PMAR(I),ESTER(I)
   14 WRITE(2,13)I,PMAR(I),ESTER(I)
C PMAR=PROFIT MARGIN
C ESTER=ESTIMATION ERROR
   15 FORMAT(F10.3,F10.3)
      N=0
      TOTP=0
      ISUM=0
      DO 3 ID=1,IE
      EXTERNAL RANDY
      CALL LEBIDDER(RANDY)
    3 CONTINUE
C ISUM=NO OF BIDS WON BY E IN NO OF COMPARED CONTRACTS
C TOTP=E TOTAL PROFIT FOR ALL WON CONTRACTS
C AVNETP=E AVERAGE NET PROFIT PER WON CONTRACT
      AVNETP=TOTP/ISUM
C SUC=E PERCENTAGE SUCCESS IN NO OF COMPARED CONTRACTS
      SUC=(100.0*ISUM)/IE
      WRITE(2,9) SUC
      WRITE(2,16)AVNETP
    5 FORMAT(I7,I7)
    9 FORMAT(20H ESUCCESS PERCENT = ,F10.3,/)
   13 FORMAT(I7,F10.3,F10.3)
   16 FORMAT(22H AVERAGE NET PROFIT = ,F10.3,//)
   17 FORMAT(I7)
   19 FORMAT(14H JOB NUMBER : ,I7,/)
   25 FORMAT(29H  BIDDER    PROFMAR  ESTERROR)
   18 CONTINUE
      STOP
      END
      SUBROUTINE RANDY(RANDO)
      COMMON N,IC,PMAR,ISUM,TOTP,ESTER
      INTEGER FACTOR
      N=N+1
      IF(N.GT.1) GOTO 10
      RNEXT=1025.0
   10 RLAST=RNEXT
```

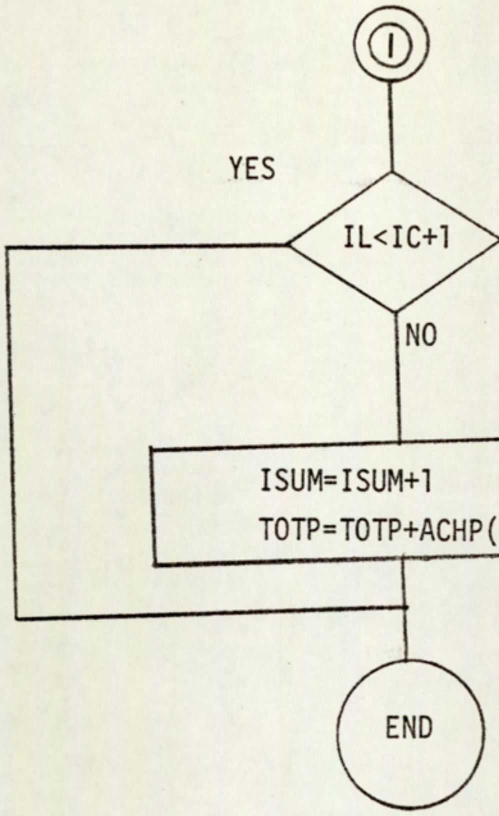
```
      NUM1=2**18
      K=83
      PRODUCT=K*RLAST
      FACTOR=INT(PRODUCT/NUM1)
      RNEXT=PRODUCT-FLOAT(FACTOR)*FLOAT(NUM1)
      RANDO=RNEXT/NUM1
      RETURN
      END
      SUBROUTINE LERIDDER(RANDY)
      DIMENSION PC(50),TEND(50),ACHP(50),ESTER(50),PMAR(50)
      COMMON N,IC,PMAR,ISUM,TOTP,ESTER
      DO 12 J=1,IC+1
 2    CALL RANDY(R1)
      A=R1
      CALL RANDY (R2)
      B=R2
      U=((-2*ALOG(A))**0.5)*COS(2*3.14159*B)
      IF(U.GT.3.0) U=3.0
      IF(U.LT.-3.0) U=-3.0
      PC(J)=100+(ESTER(J)/3)*U
      TEND(J)=PC(J)*(1+PMAR(J))
      ACHP(J)=TEND(J)-100
 12   CONTINUE
 31   IS=1
      DO 20 I=2,IC+1
      IF(TEND(IS)-TEND(I))21,22,22
 21   IL=IS
      GO TO 20
 22   IS=I
      IL=I
 20   CONTINUE
      IF(IL.LT.IC+1)GOTO 11
      ISUM=ISUM+1
      TOTP=TOTP+ACHP(IL)
 11   CONTINUE
      RETURN
      END
      FINISH
```

C) Normally distributed estimation accuracy $2\sigma = \pm ER\%$.

Subroutine LEBIDDER is the same as that in the previous section except that $2\sigma = \pm ER\%$.

Following is its flow chart:


START
J=1 (1) IC+1
CALL RANDY(R1)
A=R1
CALL RANDY (R2)
B=R2
U=((-2*ALOG(A))**0.5)*COS(2*3.14159*B)
U>3.0
Yes
U=3.0
NO
U<-3.0
NO
YES
U=-3.0
PC(J)=100*(ESTER(J)/2)*U
TEND(J)=PC(J)*(1+PMAR(J))
ACHP(J)=TEND(J)-100
IS=1
I=2 (1) IC+1
YES
TEND(IS)<
TEND(I)
IL=IS
NO
TEND(IS) >
TEND(I)
Yes
NO
IS=I
IL=I
1


1
YES
IL<IC+1
NO
ISUM=ISUM+1
TOTP=TOTP+ACHP(IL)
END

```
      MASTER ALI
      DIMENSION PMAR(50),ESTER(50)
      COMMON N,IC,PMAR,ISUM,TOTP,ESTER
      READ(1,17)NJOB
C NJOB=NO OF JOBS EACH WITH DIFF PARAMETERS
      DO 18 K=1,NJOB
      WRITE(2,19)K
      READ (1,5)IE,IC
C IE=NO OF COMPARED CONTRACTS
C IC=NO OF COMPETITORS PER CONTRACT
      WRITE(2,25)
      DO 14 I=1,IC+1
      READ(1,15)PMAR(I),ESTER(I)
   14 WRITE(2,13)I,PMAR(I),ESTER(I)
C PMAR=PROFIT MARGIN
C ESTER=ESTIMATION ERROR
   15 FORMAT(F10.3,F10.3)
      N=0
      TOTP=0
      ISUM=0
      DO 3 ID=1,IE
      EXTERNAL RANDY
      CALL LEBIDDER(RANDY)
    3 CONTINUE
C ISUM=NO OF BIDS WON BY E IN NO OF COMPARED CONTRACTS
C TOTP=E TOTAL PROFIT FOR ALL WON CONTRACTS
C AVNETP=E AVERAGE NET PROFIT PER WON CONTRACT
      AVNETP=TOTP/ISUM
C SUC=E PERCENTAGE SUCCESS IN NO OF COMPARED CONTRACTS
      SUC=(100.0*ISUM)/IE
      WRITE(2,9) SUC
      WRITE(2,16)AVNETP
    5 FORMAT(I7,I7)
    9 FORMAT(20H ESUCCESS PERCENT = ,F10.5,/)
   13 FORMAT(I7,F10.3,F10.3)
   16 FORMAT(22H AVERAGE NET PROFIT = ,F10.3,//)
   17 FORMAT(I7)
   19 FORMAT(14H JOB NUMBER : ,I7,/)
   25 FORMAT(29H  BIDDER    PROFMAR  ESTERROR)
   18 CONTINUE
      STOP
      END
      SUBROUTINE RANDY(RANDO)
      COMMON N,IC,PMAR,ISUM,TOTP,ESTER
      INTEGER FACTOR
      N=N+1
      IF(N.GT.1) GOTO 10
      RNEXT=1023.0
   10 RLAST=RNEXT
```

```
      NUM1=2**18
      K=83
      PRODUCT=K*RLAST
      FACTOR=INT(PRODUCT/NUM1)
      RNEXT=PRODUCT-FLOAT(FACTOR)*FLOAT(NUM1)
      RANDO=RNEXT/NUM1
      RETURN
      END
      SUBROUTINE LERIDDER(RANDY)
      DIMENSION PC(50),TEND(50),ACHP(50),ESTER(50),PMAR(50)
      COMMON N,IC,PMAR,ISUM,TOTP,ESTER
      DO 12 J=1,IC+1
    2 CALL RANDY(R1)
      A=R1
      CALL RANDY(R2)
      B=R2
      U=((-2*ALOG(A))**0.5)*COS(2*3.14159*B)
      IF(U.GT.3.0) U=3.0
      IF(U.LT.-3.0) U=-3.0
      PC(J)=100+(ESTER(J)/2)*U
      TEND(J)=PC(J)*(1+PMAR(J))
      ACHP(J)=TEND(J)-100
   12 CONTINUE
   31 IS=1
      DO 20 I=2,IC+1
      IF(TEND(IS)-TEND(I))21,22,22
   21 IL=IS
      GO TO 20
   22 IS=I
      IL=I
   20 CONTINUE
      IF(IL.LT.IC+1)GOTO 11
      ISUM=ISUM+1
      TOTP=TOTP+ACHP(IL)
   11 CONTINUE
      RETURN
      END
      FINISH
```

7.2.4 Programs for simulations with variable job value

A) Uniformly distributed estimation accuracy:

The master segment consists of the following steps:

1) The PRN generation subroutine of the NAG Library is initialized.

2) The number of simulations are read.

3) A loop around the number of contractors (five) is constructed and the profit-margin and estimation accuracy of each one is read.

4) An integer to initialize subroutine RANDY is set to zero.

5) A loop around the number of years is constructed.

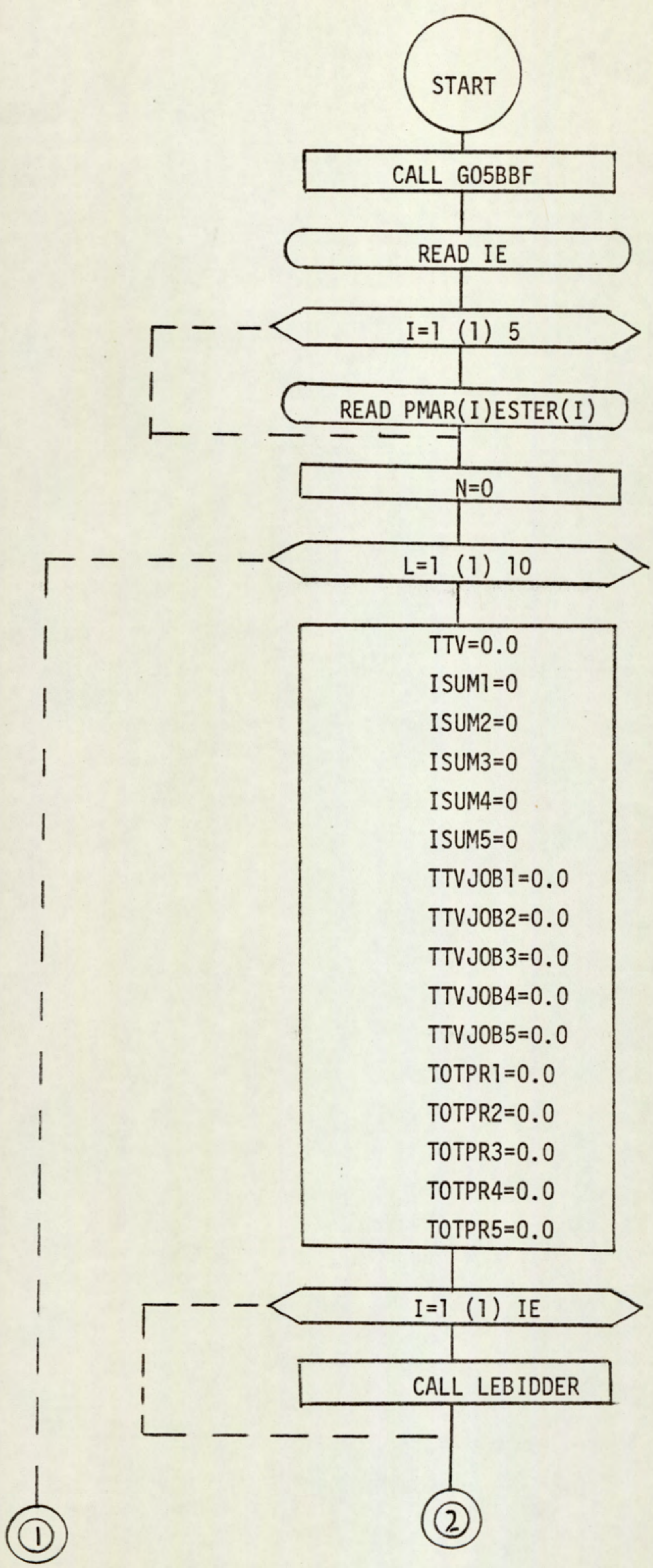
6) The total tenders values and the number of contracts won, total value of contracts, and the total profit for each contractor are initialized.

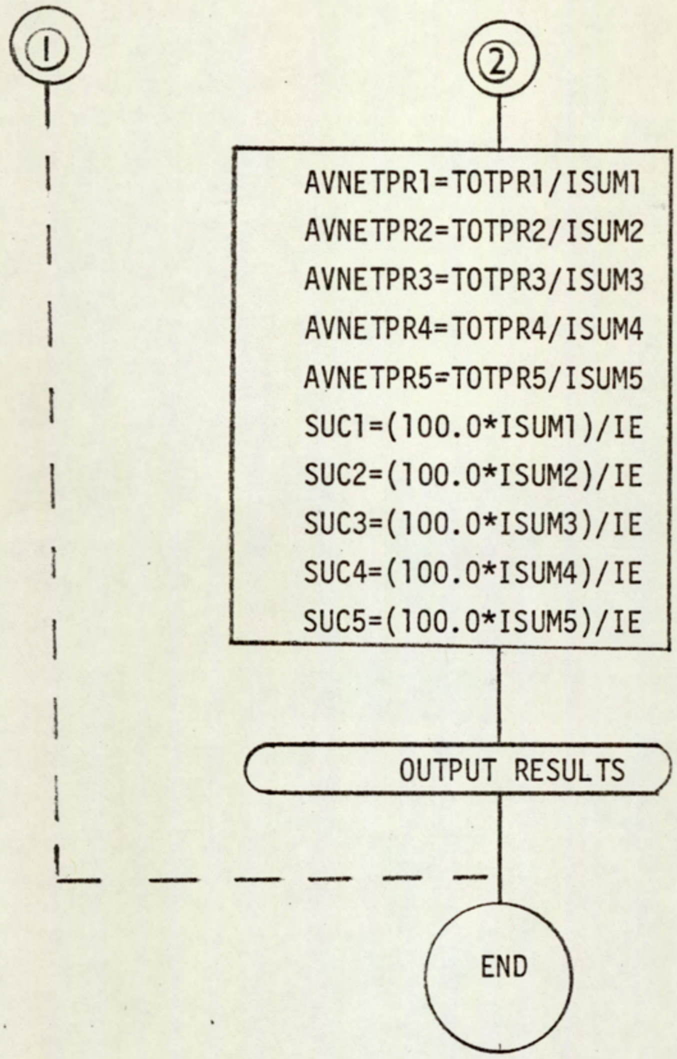
7) A loop around the number of simulations is constructed and subroutine LEBIDDER is called each time.

8) The average net profit and the success ratio of each contractor are evaluated.

9) The results are outputed.

Following is the flow chart of the master segment:


START
CALL G05BBF
READ IE
I=1 (1) 5
READ PMAR(I)ESTER(I)
N=0
L=1 (1) 10
TTV=0.0
ISUM1=0
ISUM2=0
ISUM3=0
ISUM4=0
ISUM5=0
TTVJOB1=0.0
TTVJOB2=0.0
TTVJOB3=0.0
TTVJOB4=0.0
TTVJOB5=0.0
TOTPR1=0.0
TOTPR2=0.0
TOTPR3=0.0
TOTPR4=0.0
TOTPR5=0.0
I=1 (1) IE
CALL LEBIDDER
1
2


1
2
AVNETPR1=TOTPR1/ISUM1
AVNETPR2=TOTPR2/ISUM2
AVNETPR3=TOTPR3/ISUM3
AVNETPR4=TOTPR4/ISUM4
AVNETPR5=TOTPR5/ISUM5
SUC1=(100.0*ISUM1)/IE
SUC2=(100.0*ISUM2)/IE
SUC3=(100.0*ISUM3)/IE
SUC4=(100.0*ISUM4)/IE
SUC5=(100.0*ISUM5)/IE
OUTPUT RESULTS
END

Subroutine LEBIDDER is similar to that of the fixed job value except that it samples a value for the job value from a uniform distribution with limits of £50K and £1000K. Following are the steps followed:

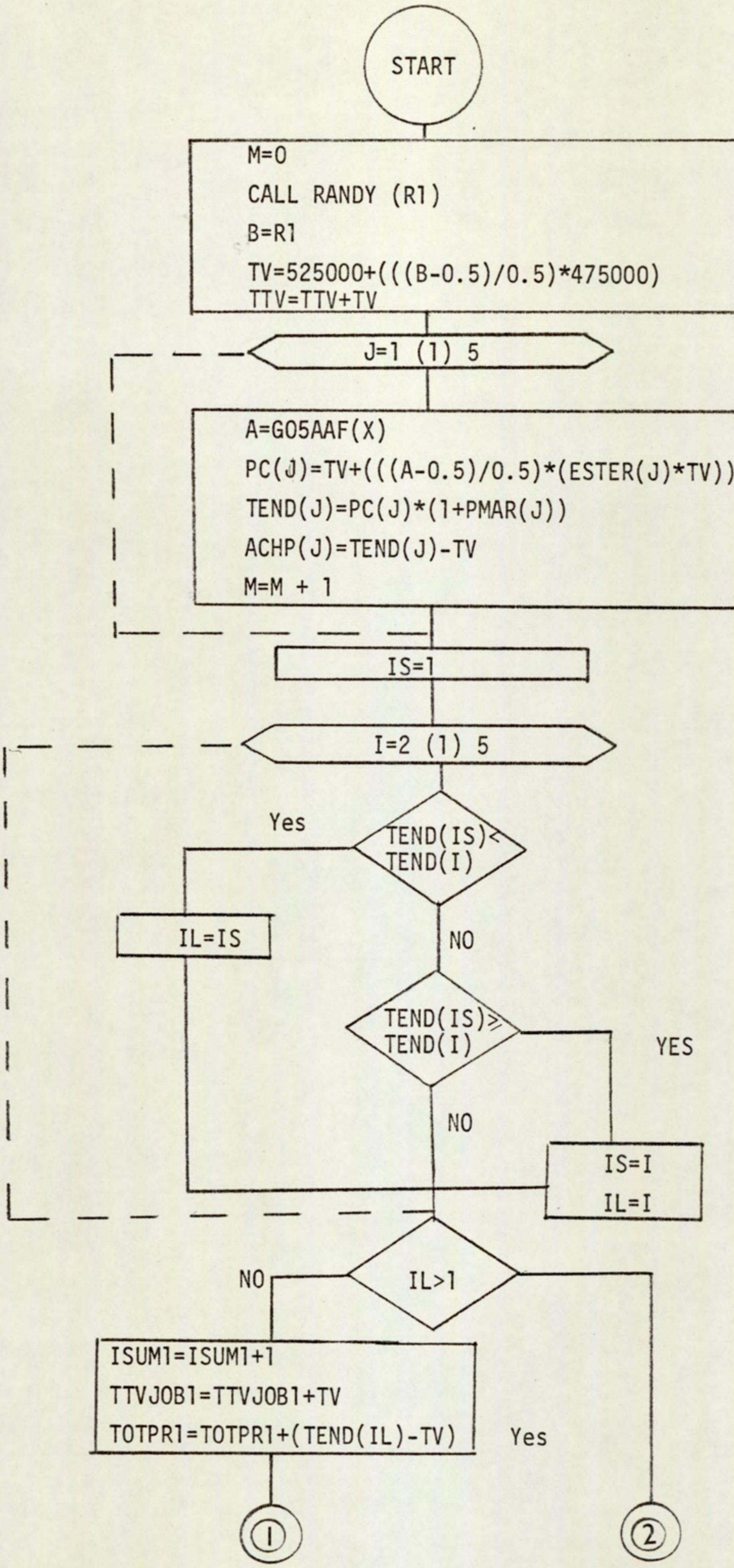
1) Subroutine RANDY is called and a tender value is sampled from a uniform distribution between £50K and £1000K.

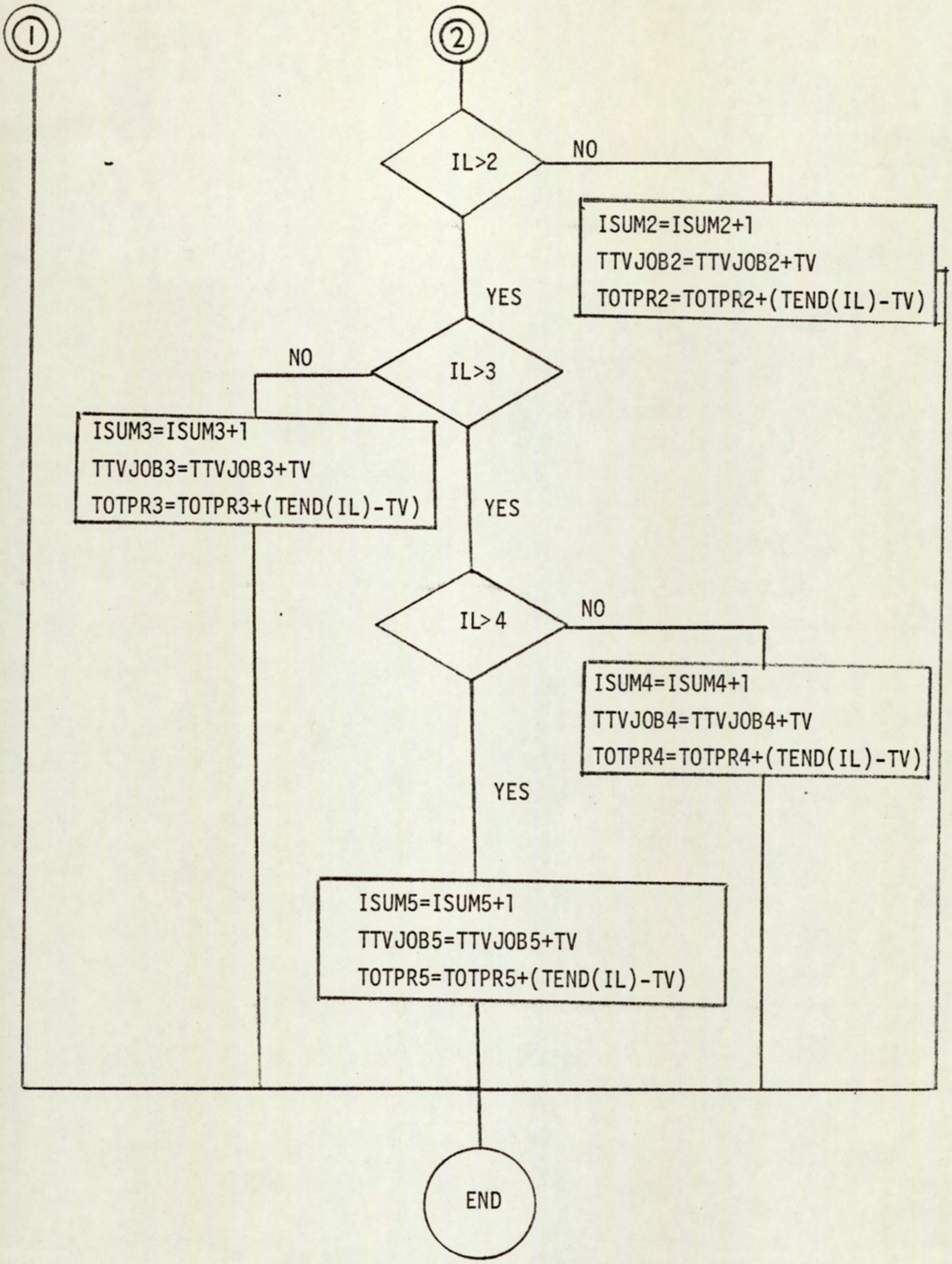
2) A loop around the number of contractors is constructed and the PRN generation subroutine of the NAG Library is called. The estimation accuracy of each contractor is sampled from a uniform distribution and the tender value and achieved profit are calculated.

3) A comparison is conducted to find the winning contractor.

4) For the winning contractor, the number of won contracts is increased by one, the total value of contracts won is increased by the amount of the new tender value, and the total profit is increased by the achieved profit of the new contract.

Following is the flow chart of subroutine LEBIDDER:


START
M=0
CALL RANDY (R1)
B=R1
TV=525000+(((B-0.5)/0.5)*475000)
TTV=TTV+TV
J=1 (1) 5
A=G05AAF(X)
PC(J)=TV+(((A-0.5)/0.5)*(ESTER(J)*TV))
TEND(J)=PC(J)*(1+PMAR(J))
ACHP(J)=TEND(J)-TV
M=M + 1
IS=1
I=2 (1) 5
Yes
TEND(IS)<
TEND(I)
IL=IS
NO
TEND(IS)≥
TEND(I)
YES
NO
IS=I
IL=I
NO
IL>1
ISUM1=ISUM1+1
TTVJOB1=TTVJOB1+TV
TOTPR1=TOTPR1+(TEND(IL)-TV)
Yes
1
2


1
2
IL>2
NO
ISUM2=ISUM2+1
TTVJOB2=TTVJOB2+TV
TOTPR2=TOTPR2+(TEND(IL)-TV)
YES
IL>3
NO
ISUM3=ISUM3+1
TTVJOB3=TTVJOB3+TV
TOTPR3=TOTPR3+(TEND(IL)-TV)
YES
IL>4
NO
ISUM4=ISUM4+1
TTVJOB4=TTVJOB4+TV
TOTPR4=TOTPR4+(TEND(IL)-TV)
YES
ISUM5=ISUM5+1
TTVJOB5=TTVJOB5+TV
TOTPR5=TOTPR5+(TEND(IL)-TV)
END

```
      TRACE 2
      MASTER VARTEN
      DIMENSION PMAR(50),ESTER(50)
      COMMON M,N,ESTER,PMAR,ISUM1,ISUM2,ISUM3,ISUM4,ISUM5,
     *TTVJOB1,TTVJOB2,TTVJOB3,TTVJOB4,TTVJOB5,
     *TOTPR1,TOTPR2,TOTPR3,TOTPR4,TOTPR5,TTV
      CALL G05BBF
      READ(1,5)IE
      DO 6 I=1,5
6     READ(1,7) PMAR(I),ESTER(I)
      N=0
      DO 39 L=1,10
      TTV=0.0
      ISUM1=0
      ISUM2=0
      ISUM3=0
      ISUM4=0
      ISUM5=0
      TTVJOB1=0.0
      TTVJOB2=0.0
      TTVJOB3=0.0
      TTVJOB4=0.0
      TTVJOB5=0.0
      TOTPR1=0.0
      TOTPR2=0.0
      TOTPR3=0.0
      TOTPR4=0.0
      TOTPR5=0.0
      DO 3 I=1,IE
      EXTERNAL RANDY,G05AAF
      CALL LEBIDDER(RANDY,G05AAF)
3     CONTINUE
      AVNETPR1=TOTPR1/ISUM1
      AVNETPR2=TOTPR2/ISUM2
      AVNETPR3=TOTPR3/ISUM3
      AVNETPR4=TOTPR4/ISUM4
      AVNETPR5=TOTPR5/ISUM5
      SUC1=(100.0*ISUM1)/IE
      SUC2=(100.0*ISUM2)/IE
      SUC3=(100.0*ISUM3)/IE
      SUC4=(100.0*ISUM4)/IE
      SUC5=(100.0*ISUM5)/IE
      WRITE(2,41)TTV
      WRITE(2,42)TTVJOB1
      WRITE(2,43)TTVJOB2
      WRITE(2,44)TTVJOB3
      WRITE(2,45)TTVJOB4
      WRITE(2,46)TTVJOB5
      WRITE(2,61)TOTPR1
```

```
      WRITE(2,62)TOTPR2
      WRITE(2,63)TOTPR3
      WRITE(2,64)TOTPR4
      WRITE(2,65)TOTPR5
      WRITE(2,71)AVNETPR1
      WRITE(2,72)AVNETPR2
      WRITE(2,73)AVNETPR3
      WRITE(2,74)AVNETPR4
      WRITE(2,75)AVNETPR5
      WRITE(2,81)SUC1
      WRITE(2,82)SUC2
      WRITE(2,83)SUC3
      WRITE(2,84)SUC4
      WRITE(2,85)SUC5
41    FORMAT(30H SUM OF CONTRACTS TRUE COST = ,F10.3,//)
42    FORMAT(18H SUM WON BY NO1 = ,F10.3,/)
43    FORMAT(18H SUM WON BY NO2 = ,F10.3,/)
44    FORMAT(18H SUM WON BY NO3 = ,F10.3,/)
45    FORMAT(18H SUM WON BY NO4 = ,F10.3,/)
46    FORMAT(18H SUM WON BY NO5 = ,F10.3,/)
   61 FORMAT(21H PROFIT SUM OF NO1 = ,F10.3,/)
   62 FORMAT(21H PROFIT SUM OF NO2 = ,F10.3,/)
   63 FORMAT(21H PROFIT SUM OF NO3 = ,F10.3,/)
   64 FORMAT(21H PROFIT SUM OF NO4 = ,F10.3,/)
   65 FORMAT(21H PROFIT SUM OF NO5 = ,F10.3,/)
   71 FORMAT(26H AVERAGE NET PROFIT NO1 = ,F10.3,/)
   72 FORMAT(26H AVERAGE NET PROFIT NO2 = ,F10.3,/)
   73 FORMAT(26H AVERAGE NET PROFIT NO3 = ,F10.3,/)
   74 FORMAT(26H AVERAGE NET PROFIT NO4 = ,F10.3,/)
   75 FORMAT(26H AVERAGE NET PROFIT NO5 = ,F10.3,/)
81    FORMAT(21H SUCCESS RATIO NO1 = ,F10.3,/)
82    FORMAT(21H SUCCESS RATIO NO2 = ,F10.3,/)
83    FORMAT(21H SUCCESS RATIO NO3 = ,F10.3,/)
84    FORMAT(21H SUCCESS RATIO NO4 = ,F10.3,/)
85    FORMAT(21H SUCCESS RATIO NO5 = ,F10.3,/)
 5    FORMAT(I7)
 7    FORMAT(F6.2,F6.2)
39    CONTINUE
      STOP
      END
      SUBROUTINE RANDY(RANDO)
      COMMON M,N,ESTER,PMAR,ISUM1,ISUM2,ISUM3,ISUM4,ISUM5,
     *TTVJOB1,TTVJOB2,TTVJOB3,TTVJOB4,TTVJOB5,
     *TOTPR1,TOTPR2,TOTPR3,TOTPR4,TOTPR5,TTV
      INTEGER FACTOR
      N=N+1
      IF(N.GT.1) GOTO 10
      RNEXT=1023.0
   10 RLAST=RNEXT
      NUM1=2**18
      K=83
      PRODUCT=K*RLAST
      FACTOR=INT(PRODUCT/NUM1)
      RNEXT=PRODUCT-FLOAT(FACTOR)*FLOAT(NUM1)
      RANDO=RNEXT/NUM1
      RETURN
      END
```

```
      SUBROUTINE LERIDDER(RANDY,G05AAF)
      DIMENSION PC(50),TEND(50),ACHP(50),ESTER(50),PMAR(50)
      COMMON M,N,ESTER,PMAR,ISUM1,ISUM2,ISUM3,ISUM4,ISUM5,
     *TTVJOB1,TTVJOB2,TTVJOB3,TTVJOB4,TTVJOB5,
     *TOTPR1,TOTPR2,TOTPR3,TOTPR4,TOTPR5,TTV
      M=0
      CALL RANDY(R1)
      B=R1
      TV=525000+(((B-0.5)/0.5)*475000)
      TTV=TTV+TV
      DO 8 J=1,5
  2   A=G05AAF(X)
      PC(J)=TV+(((A-0.5)/0.5)*(ESTER(J)*TV))
      TEND(J)=PC(J)*(1+PMAR(J))
      ACHP(J)=TEND(J)-TV
      M=M+1
  8   CONTINUE
 31   IS=1
      DO 20 I=2,5
      IF(TEND(IS)-TEND(I))21,22,22
   21 IL=IS
      GO TO 20
   22 IS=I
      IL=I
   20 CONTINUE
      IF(IL.GT.1)GOTO 91
      ISUM1=ISUM1+1
      TTVJOB1=TTVJOB1+TV
      TOTPR1=TOTPR1+(TEND(IL)-TV)
      GOTO 11
 91   IF(IL.GT.2) GOTO 92
      ISUM2=ISUM2+1
      TTVJOB2=TTVJOB2+TV
      TOTPR2=TOTPR2+(TEND(IL)-TV)
      GOTO 11
 92   IF(IL.GT.3) GOTO 93
      ISUM3=ISUM3+1
      TTVJOB3=TTVJOB3+TV
      TOTPR3=TOTPR3+(TEND(IL)-TV)
      GOTO 11
   93 IF(IL.GT.4) GOTO 94
      ISUM4=ISUM4+1
      TTVJOB4=TTVJOB4+TV
      TOTPR4=TOTPR4+(TEND(IL)-TV)
      GOTO 11
 94   ISUM5=ISUM5+1
      TTVJOB5=TTVJOB5+TV
      TOTPR5=TOTPR5+(TEND(IL)-TV)
 11   CONTINUE
      RETURN
      END
      FINISH
```

B) Normally distributed estimation accuracy $3\sigma = \pm$ ER%.

The master segment is the same as section (A) but subroutine LEBIDDER differs by sampling the estimation accuracy from a normal distribution with $3\sigma = \pm$ ER% similar to section (B) of (7.2.3), therefore the flow chart of this subroutine will not be presented.

```
      TRACE 2
      MASTER VARTEN
      DIMENSION PMAR(50),ESTER(50)
      COMMON M,N,ESTER,PMAR,ISUM1,ISUM2,ISUM3,ISUM4,ISUM5,
     *TTVJOB1,TTVJOB2,TTVJOB3,TTVJOB4,TTVJOB5,
     *TOTPR1,TOTPR2,TOTPR3,TOTPR4,TOTPR5,TTV
      CALL G05BBF
      READ(1,5)IE
      DO 6 I=1,5
    6 READ(1,7) PMAR(I),ESTER(I)
      N=0
      DO 39 L=1,10
      TTV=0.0
      ISUM1=0
      ISUM2=0
      ISUM3=0
      ISUM4=0
      ISUM5=0
      TTVJOB1=0.0
      TTVJOB2=0.0
      TTVJOB3=0.0
      TTVJOB4=0.0
      TTVJOB5=0.0
      TOTPR1=0.0
      TOTPR2=0.0
      TOTPR3=0.0
      TOTPR4=0.0
      TOTPR5=0.0
      DO 3 I=1,IE
      EXTERNAL RANDY,G05AAF
      CALL LEBIDDER(RANDY,G05AAF)
    3 CONTINUE
      AVNETPR1=TOTPR1/ISUM1
      AVNETPR2=TOTPR2/ISUM2
      AVNETPR3=TOTPR3/ISUM3
      AVNETPR4=TOTPR4/ISUM4
      AVNETPR5=TOTPR5/ISUM5
      SUC1=(100.0*ISUM1)/IE
      SUC2=(100.0*ISUM2)/IE
      SUC3=(100.0*ISUM3)/IE
      SUC4=(100.0*ISUM4)/IE
      SUC5=(100.0*ISUM5)/IE
      WRITE(2,41)TTV
      WRITE(2,42)TTVJOB1
      WRITE(2,43)TTVJOB2
      WRITE(2,44)TTVJOB3
      WRITE(2,45)TTVJOB4
      WRITE(2,46)TTVJOB5
      WRITE(2,61)TOTPR1
```

```
      WRITE(2,62)TOTPR2
      WRITE(2,63)TOTPR3
      WRITE(2,64)TOTPR4
      WRITE(2,65)TOTPR5
      WRITE(2,71)AVNETPR1
      WRITE(2,72)AVNETPR2
      WRITE(2,73)AVNETPR3
      WRITE(2,74)AVNETPR4
      WRITE(2,75)AVNETPR5
      WRITE(2,81)SUC1
      WRITE(2,82)SUC2
      WRITE(2,83)SUC3
      WRITE(2,84)SUC4
      WRITE(2,85)SUC5
41    FORMAT(30H SUM OF CONTRACTS TRUE COST = ,F10.3,//)
42    FORMAT(18H SUM WON BY NO1 = ,F10.3,/)
43    FORMAT(18H SUM WON BY NO2 = ,F10.3,/)
44    FORMAT(18H SUM WON BY NO3 = ,F10.3,/)
45    FORMAT(18H SUM WON BY NO4 = ,F10.3,/)
46    FORMAT(18H SUM WON BY NO5 = ,F10.3,/)
   61 FORMAT(21H PROFIT SUM OF NO1 = ,F10.3,/)
   62 FORMAT(21H PROFIT SUM OF NO2 = ,F10.3,/)
   63 FORMAT(21H PROFIT SUM OF NO3 = ,F10.3,/)
   64 FORMAT(21H PROFIT SUM OF NO4 = ,F10.3,/)
   65 FORMAT(21H PROFIT SUM OF NO5 = ,F10.3,/)
   71 FORMAT(26H AVERAGE NET PROFIT NO1 = ,F10.3,/)
   72 FORMAT(26H AVERAGE NET PROFIT NO2 = ,F10.3,/)
   73 FORMAT(26H AVERAGE NET PROFIT NO3 = ,F10.3,/)
   74 FORMAT(26H AVERAGE NET PROFIT NO4 = ,F10.3,/)
   75 FORMAT(26H AVERAGE NET PROFIT NO5 = ,F10.3,/)
81    FORMAT(21H SUCCESS RATIO NO1 = ,F10.3,/)
82    FORMAT(21H SUCCESS RATIO NO2 = ,F10.3,/)
83    FORMAT(21H SUCCESS RATIO NO3 = ,F10.3,/)
84    FORMAT(21H SUCCESS RATIO NO4 = ,F10.3,/)
85    FORMAT(21H SUCCESS RATIO NO5 = ,F10.3,/)
 5    FORMAT(I7)
 7    FORMAT(F6.2,F6.2)
39    CONTINUE
      STOP
      END
      SUBROUTINE RANDY(RANDO)
      COMMON M,N,ESTER,PMAR,ISUM1,ISUM2,ISUM3,ISUM4,ISUM5,
     *TTVJOB1,TTVJOB2,TTVJOB3,TTVJOB4,TTVJOB5,
     *TOTPR1,TOTPR2,TOTPR3,TOTPR4,TOTPR5,TTV
      INTEGER FACTOR
      N=N+1
      IF(N.GT.1) GOTO 10
      RNEXT=1023.0
   10 RLAST=RNEXT
      NUM1=2**18
      K=83
      PRODUCT=K*RLAST
      FACTOR=INT(PRODUCT/NUM1)
      RNEXT=PRODUCT-FLOAT(FACTOR)*FLOAT(NUM1)
      RANDO=RNEXT/NUM1
      RETURN
      END
```

```
      SUBROUTINE LERIDDER(RANDY,G05AAF)
      DIMENSION PC(50),TEND(50),ACHP(50),ESTER(50),PMAR(50)
      COMMON M,N,ESTER,PMAR,ISUM1,ISUM2,ISUM3,ISUM4,ISUM5,
     *TTVJOB1,TTVJOB2,TTVJOB3,TTVJOB4,TTVJOB5,
     *TOTPR1,TOTPR2,TOTPR3,TOTPR4,TOTPR5,TTV
      M=0
      CALL RANDY(R1)
      B=R1
      TV=525000+(((B-0.5)/0.5)*475000)
      TTV=TTV+TV
      DO 8 J=1,5
  2   A=G05AAF(X)
      C=G05AAF(X)
      U=((-2*ALOG(A))**0.5)*COS(2*3.14159*C)
      IF(U.GT.3.0) U=3
      IF(U.LT.-3.0) U=-3.0
      PC(J)=TV+(ESTER(J)/3)*U*TV
      TEND(J)=PC(J)*(1+PMAR(J))
      ACHP(J)=TEND(J)-TV
      M=M+1
  8   CONTINUE
 31   IS=1
      DO 20 I=2,5
      IF(TEND(IS)-TEND(I))21,22,22
  21  IL=IS
      GO TO 20
  22  IS=I
      IL=I
  20  CONTINUE
      IF(IL.GT.1)GOTO 91
      ISUM1=ISUM1+1
      TTVJOB1=TTVJOB1+TV
      TOTPR1=TOTPR1+(TEND(IL)-TV)
      GOTO 11
 91   IF(IL.GT.2) GOTO 92
      ISUM2=ISUM2+1
      TTVJOB2=TTVJOB2+TV
      TOTPR2=TOTPR2+(TEND(IL)-TV)
      GOTO 11
 92   IF(IL.GT.3) GOTO 93
      ISUM3=ISUM3+1
      TTVJOB3=TTVJOB3+TV
      TOTPR3=TOTPR3+(TEND(IL)-TV)
      GOTO 11
  93  IF(IL.GT.4) GOTO 94
      ISUM4=ISUM4+1
      TTVJOB4=TTVJOB4+TV
      TOTPR4=TOTPR4+(TEND(IL)-TV)
      GOTO 11
  94  ISUM5=ISUM5+1
      TTVJOB5=TTVJOB5+TV
      TOTPR5=TOTPR5+(TEND(IL)-TV)
 11   CONTINUE
      RETURN
      END
      FINISH
```

7.2.5 The program for the application of the concept of target probability

The estimation accuracy in this program is sampled from a uniform distribution, therefore subroutine LEBIDDER is similar to that of section (7.2.4)A. The steps of the master segment are as follows.

1) The PRN generation subroutine of the NAG Library is called from the computer store.

2) The number of simulations for the period of comparison is read. It is assumed that 48 tenders are bid for each year, therefore, for 6 months, 3 months, and 6 weeks, the number of simulations are 24, 12 and 6 respectively.

3) A loop around the number of contractors is constructed and the profit margin and estimation accuracy of each one is read.

4) An integer initialize subroutine RANDY is set to zero.

5) A loop around the number of cycles of the check time period in ten years is constructed. If the check is conducted every year this number is 10. However,if the check is conducted every 6 months, 3 months, or 6 weeks, this number is 20, 40 and 80 respectively.

6) The total tenders values and the number of contracts won, total value of contracts, and the total profit for each contractor are initialized.

7) A loop around the number of simulations and subroutine LEBIDDER is called each time.

8) The target tender value for the simulation period is set. This value is 4878860 if the simulation period is a year. If the period is 6 months, 3 months, or 6 weeks; this value is multiplied by $\frac{1}{2}$, $\frac{1}{4}$, and $\frac{1}{8}$ respectively.

9) The total value of contracts won for each contractor is evaluated.

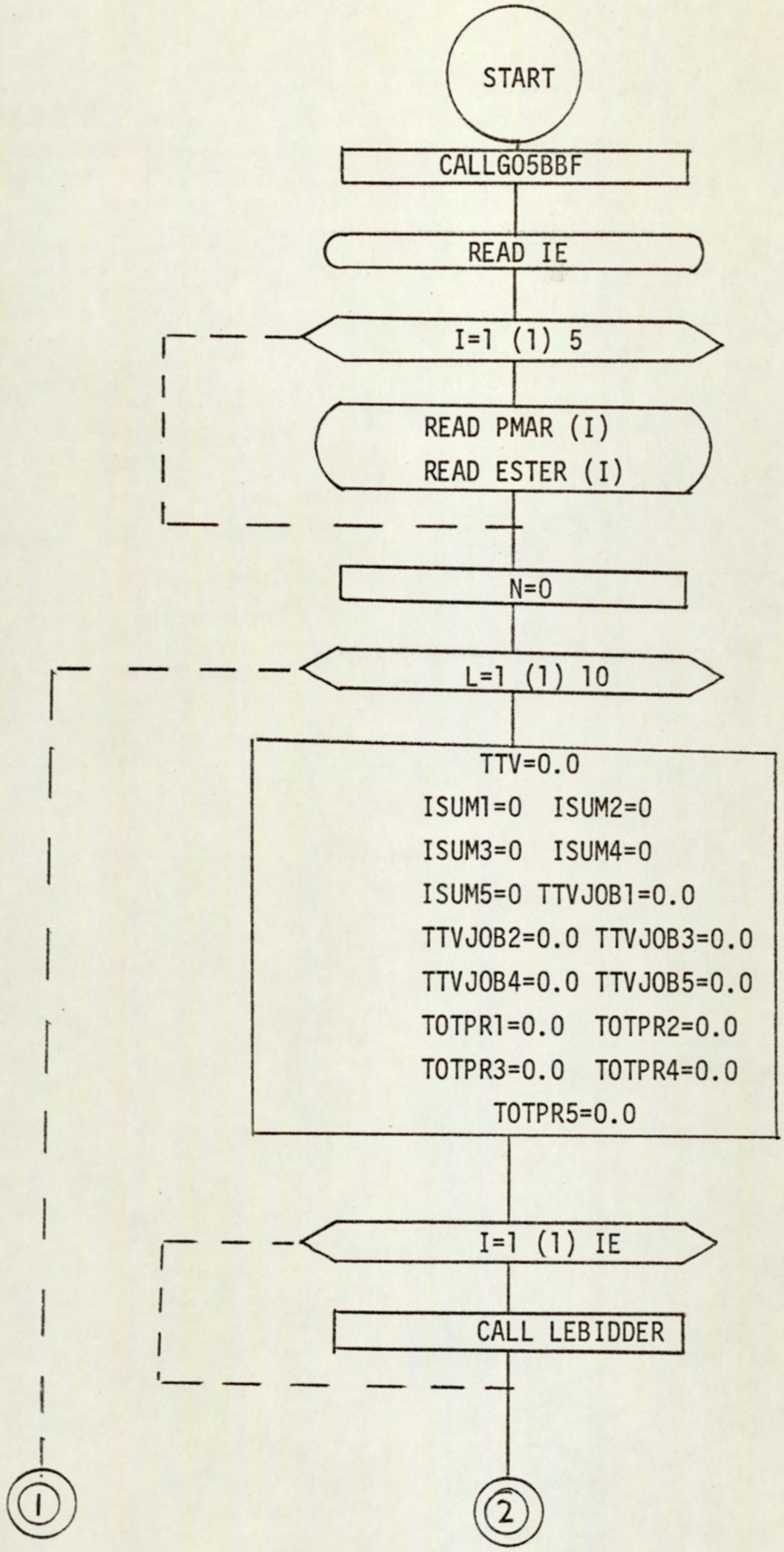
10) The value obtained from step 9 is compared with the the target value and the mark-up is adjusted simultaneously.

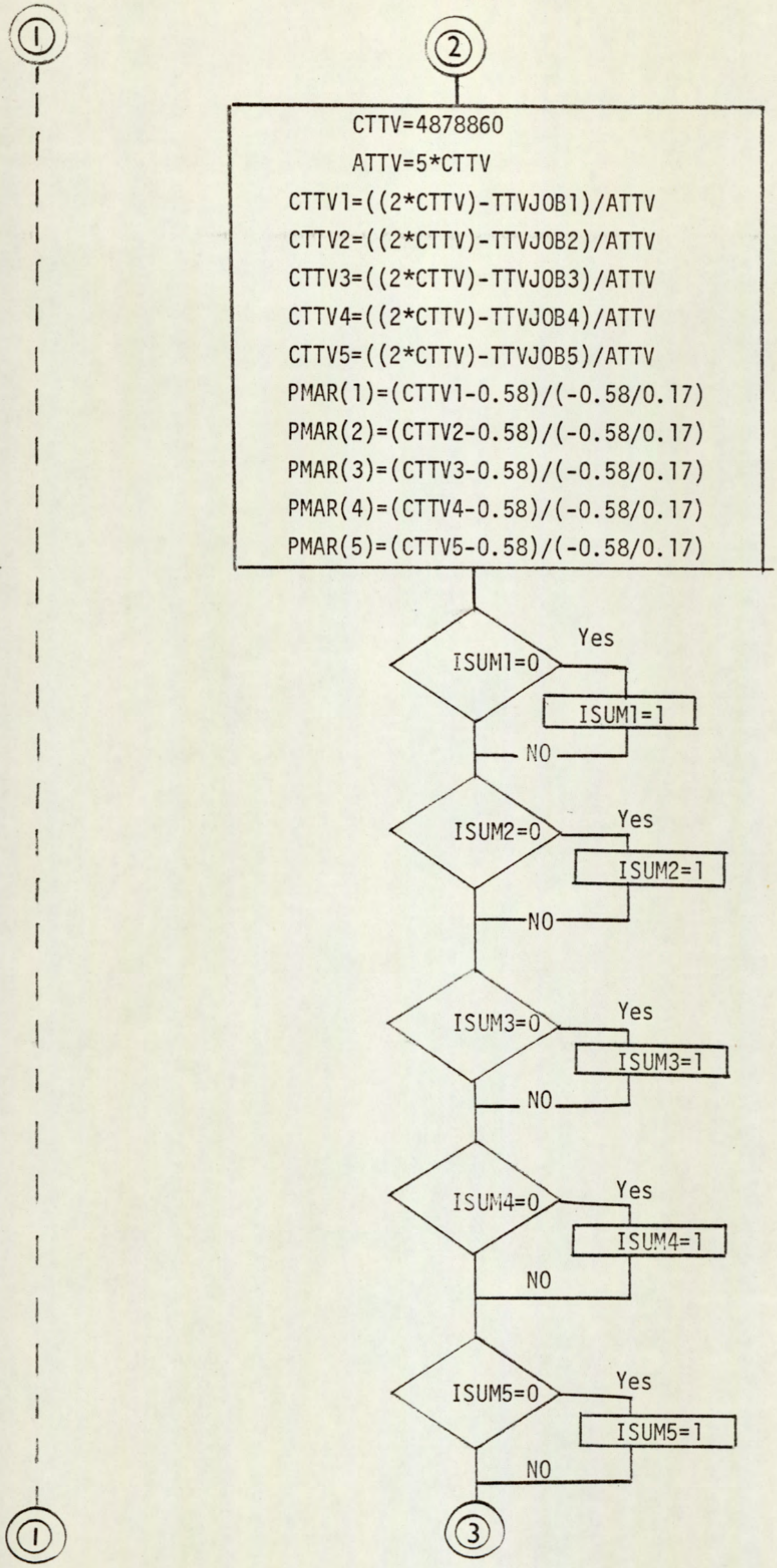
11) If the number of contracts won by any competitor is zero for this time period it is made 1 to avoid failure of the program due to overflow arising from the division by zero.

12) The average net profit and the success ratio for each contractor are evaluated.

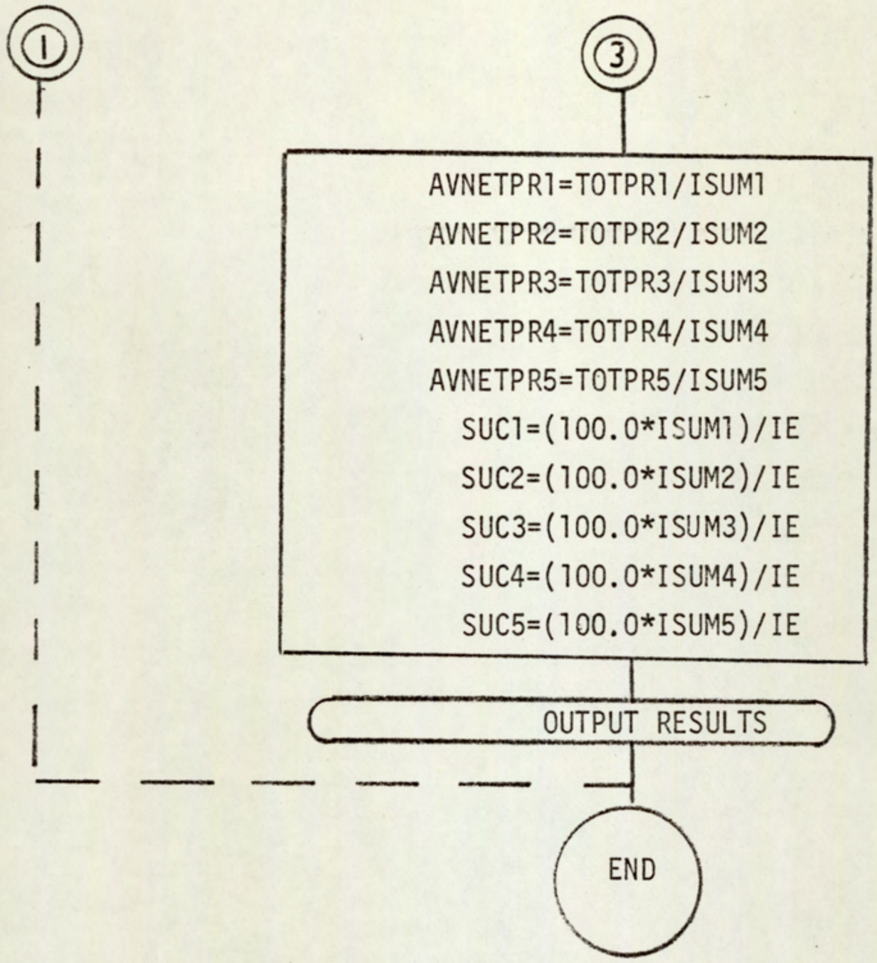
13) The results are outputed.

Following is the flow chart of the master segment.


START
CALLG05BBF
READ IE
I=1 (1) 5
READ PMAR (I)
READ ESTER (I)
N=0
L=1 (1) 10
TTV=0.0
ISUM1=0 ISUM2=0
ISUM3=0 ISUM4=0
ISUM5=0 TTVJOB1=0.0
TTVJOB2=0.0 TTVJOB3=0.0
TTVJOB4=0.0 TTVJOB5=0.0
TOTPR1=0.0 TOTPR2=0.0
TOTPR3=0.0 TOTPR4=0.0
TOTPR5=0.0
I=1 (1) IE
CALL LEBIDDER
1
2



1
2
CTTV=4878860
ATTV=5*CTTV
CTTV1=((2*CTTV)-TTVJOB1)/ATTV
CTTV2=((2*CTTV)-TTVJOB2)/ATTV
CTTV3=((2*CTTV)-TTVJOB3)/ATTV
CTTV4=((2*CTTV)-TTVJOB4)/ATTV
CTTV5=((2*CTTV)-TTVJOB5)/ATTV
PMAR(1)=(CTTV1-0.58)/(-0.58/0.17)
PMAR(2)=(CTTV2-0.58)/(-0.58/0.17)
PMAR(3)=(CTTV3-0.58)/(-0.58/0.17)
PMAR(4)=(CTTV4-0.58)/(-0.58/0.17)
PMAR(5)=(CTTV5-0.58)/(-0.58/0.17)
ISUM1=0
Yes
ISUM1=1
NO
ISUM2=0
Yes
ISUM2=1
NO
ISUM3=0
Yes
ISUM3=1
NO
ISUM4=0
Yes
ISUM4=1
NO
ISUM5=0
Yes
ISUM5=1
NO
1
3


1
3
AVNETPR1=TOTPR1/ISUM1
AVNETPR2=TOTPR2/ISUM2
AVNETPR3=TOTPR3/ISUM3
AVNETPR4=TOTPR4/ISUM4
AVNETPR5=TOTPR5/ISUM5
SUC1=(100.0*ISUM1)/IE
SUC2=(100.0*ISUM2)/IE
SUC3=(100.0*ISUM3)/IE
SUC4=(100.0*ISUM4)/IE
SUC5=(100.0*ISUM5)/IE
OUTPUT RESULTS
END

```
      TRACE 1
      TRACE 2
      MASTER VARTEN
      DIMENSION PHAR(50),ESTER(50)
      COMMON N,M,ESTER,PHAR,ISUM1,ISUM2,ISUM3,ISUM4,ISUM5,
     *TTVJOB1,TTVJOB2,TTVJOB3,TTVJOB4,TTVJOB5,
     *TOTPR1,TOTPR2,TOTPR3,TOTPR4,TOTPR5,TTV
      CALL G05BBF
      READ(1,5)IE
      DO 6 I=1,5
6     READ(1,7) PHAR(I),ESTER(I)
      N=0
      DO 39 L=1,20
      TTV=0.0
      ISUM1=0


      ISUM2=0
      ISUM3=0
      ISUM4=0
      ISUM5=0
      TTVJOB1=0.0
      TTVJOB2=0.0
      TTVJOB3=0.0
      TTVJOB4=0.0
      TTVJOB5=0.0
      TOTPR1=0.0
      TOTPR2=0.0
      TOTPR3=0.0
      TOTPR4=0.0
      TOTPR5=0.0
      DO 3 I=1,IE
      EXTERNAL RANDY,G05AAF
      CALL LEBIDDER(RANDY,G05AAF)
3     CONTINUE
      CTTV=2439429
      ATTV=5*CTTV
      CTTV1=((2*CTTV)-TTVJOB1)/ATTV
      CTTV2=((2*CTTV)-TTVJOB2)/ATTV
      CTTV3=((2*CTTV)-TTVJOB3)/ATTV
      CTTV4=((2*CTTV)-TTVJOB4)/ATTV
      CTTV5=((2*CTTV)-TTVJOB5)/ATTV
      PHAR(1)=(CTTV1-0.58)/(-0.58/0.17)
      PHAR(2)=(CTTV2-0.58)/(-0.58/0.17)
      PHAR(3)=(CTTV3-0.58)/(-0.58/0.17)
      PHAR(4)=(CTTV4-0.58)/(-0.58/0.17)
      PHAR(5)=(CTTV5-0.58)/(-0.58/0.17)
      IF(ISUM1.EQ.0) ISUM1=1
      IF(ISUM2.EQ.0) ISUM2=1
      IF(ISUM3.EQ.0) ISUM3=1
      IF(ISUM4.EQ.0) ISUM4=1
      IF(ISUM5.EQ.0) ISUM5=1
```

```
      AVNETPR1=TOTPR1/ISUM1
      AVNETPR2=TOTPR2/ISUM2
      AVNETPR3=TOTPR3/ISUM3
      AVNETPR4=TOTPR4/ISUM4
      AVNETPR5=TOTPR5/ISUM5
      SUC1=(100.0*ISUM1)/IE
      SUC2=(100.0*ISUM2)/IE
      SUC3=(100.0*ISUM3)/IE
      SUC4=(100.0*ISUM4)/IE
      SUC5=(100.0*ISUM5)/IE
      WRITE(2,41)TTV
      WRITE(2,42)TTVJOB1
      WRITE(2,43)TTVJOB2
      WRITE(2,44)TTVJOB3
      WRITE(2,45)TTVJOB4
      WRITE(2,46)TTVJOB5
      WRITE(2,61)TOTPR1
      WRITE(2,62)TOTPR2
      WRITE(2,63)TOTPR3
      WRITE(2,64)TOTPR4
      WRITE(2,65)TOTPR5
      WRITE(2,71)AVNETPR1
      WRITE(2,72)AVNETPR2
      WRITE(2,73)AVNETPR3
      WRITE(2,74)AVNETPR4
      WRITE(2,75)AVNETPR5
      WRITE(2,81)SUC1


      WRITE(2,82)SUC2
      WRITE(2,83)SUC3
      WRITE(2,84)SUC4
      WRITE(2,85)SUC5
41    FORMAT(30H SUM OF CONTRACTS TRUE COST = ,F10.3,//)
42    FORMAT(18H SUM WON BY NO1 = ,F10.3,/)
43    FORMAT(18H SUM WON BY NO2 = ,F10.3,/)
44    FORMAT(18H SUM WON BY NO3 = ,F10.3,/)
45    FORMAT(18H SUM WON BY NO4 = ,F10.3,/)
46    FORMAT(18H SUM WON BY NO5 = ,F10.3,/)
 61   FORMAT(21H PROFIT SUM OF NO1 = ,F10.3,/)
 62   FORMAT(21H PROFIT SUM OF NO2 = ,F10.3,/)
 63   FORMAT(21H PROFIT SUM OF NO3 = ,F10.3,/)
 64   FORMAT(21H PROFIT SUM OF NO4 = ,F10.3,/)
 65   FORMAT(21H PROFIT SUM OF NO5 = ,F10.3,/)
 71   FORMAT(26H AVERAGE NET PROFIT NO1 = ,F10.3,/)
 72   FORMAT(26H AVERAGE NET PROFIT NO2 = ,F10.3,/)
 73   FORMAT(26H AVERAGE NET PROFIT NO3 = ,F10.3,/)
 74   FORMAT(26H AVERAGE NET PROFIT NO4 = ,F10.3,/)
 75   FORMAT(26H AVERAGE NET PROFIT NO5 = ,F10.3,/)
```

```
81    FORMAT(21H SUCCESS RATIO NO1 = ,F10.3,/)
82    FORMAT(21H SUCCESS RATIO NO2 = ,F10.3,/)
83    FORMAT(21H SUCCESS RATIO NO3 = ,F10.3,/)
84    FORMAT(21H SUCCESS RATIO NO4 = ,F10.3,/)
85    FORMAT(21H SUCCESS RATIO NO5 = ,F10.3,/)
 5    FORMAT(I7)
 7    FORMAT(F6.2,F6.2)
39    CONTINUE
      STOP
      END


LENGTH   616, NAME  VARTER


      SUBROUTINE RANDY(RANDO)
      COMMON M,N,ESTER,PHAR,ISUM1,ISUM2,ISUM3,ISUM4,ISUM5,
     *TTVJOB1,TTVJOB2,TTVJOB3,TTVJOB4,TTVJOB5,
     *TOTPR1,TOTPR2,TOTPR3,TOTPR4,TOTPR5,TTV
      INTEGER FACTOR
      N=N+1
      IF(N.GT.1) GOTO 10
      RNEXT=1023.0
   10 RLAST=RNEXT
      NUM1=2**18
      K=83
      PRODUCT=K*RLAST
      FACTOR=INT(PRODUCT/NUM1)
      RNEXT=PRODUCT-FLOAT(FACTOR)*FLOAT(NUM1)
      RANDO=RNEXT/NUM1
      RETURN
      END


LENGTH    84, NAME  RANDY


      SUBROUTINE LEBIDDER(RANDY,G05AAF)
      DIMENSION PC(50),TEND(50),ACHP(50),ESTER(50),PHAR(50)
      COMMON M,N,ESTER,PHAR,ISUM1,ISUM2,ISUM3,ISUM4,ISUM5,
     *TTVJOB1,TTVJOB2,TTVJOB3,TTVJOB4,TTVJOB5,
     *TOTPR1,TOTPR2,TOTPR3,TOTPR4,TOTPR5,TTV


      M=0
      CALL RANDY(R1)
      B=R1
      TV=525000+(((B-0.5)/0.5)*475000)
      TTV=TTV+TV
      DO 8 J=1,5
 2    A=G05AAF(X)
```

```
      PC(J)=TV+(((A-0.5)/0.5)*(ESTER(J)*TV))
      TEND(J)=PC(J)*(1+PHAR(J))
      ACHP(J)=TEND(J)-TV
      M=M+1
 8    CONTINUE
 31   IS=1
      DO 20 I=2,5
      IF(TEND(IS)-TEND(I))21,22,22
 21   IL=IS
      GO TO 20
 22   IS=I
      IL=I
 20   CONTINUE
      IF(IL.GT.1)GOTO 91
      ISUM1=ISUM1+1
      TTVJOB1=TTVJOB1+TV
      TOTPR1=TOTPR1+(TEND(IL)-TV)
      GOTO 11
 91   IF(IL.GT.2) GOTO 92
      ISUM2=ISUM2+1
      TTVJOB2=TTVJOB2+TV
      TOTPR2=TOTPR2+(TEND(IL)-TV)
      GOTO 11
 92   IF(IL.GT.3) GOTO 93
      ISUM3=ISUM3+1
      TTVJOB3=TTVJOB3+TV
      TOTPR3=TOTPR3+(TEND(IL)-TV)
      GOTO 11
 93   IF(IL.GT.4) GOTO 94
      ISUM4=ISUM4+1
      TTVJOB4=TTVJOB4+TV
      TOTPR4=TOTPR4+(TEND(IL)-TV)
      GOTO 11
 94   ISUM5=ISUM5+1
      TTVJOB5=TTVJOB5+TV
      TOTPR5=TOTPR5+(TEND(IL)-TV)
 11   CONTINUE
      RETURN
      END
```

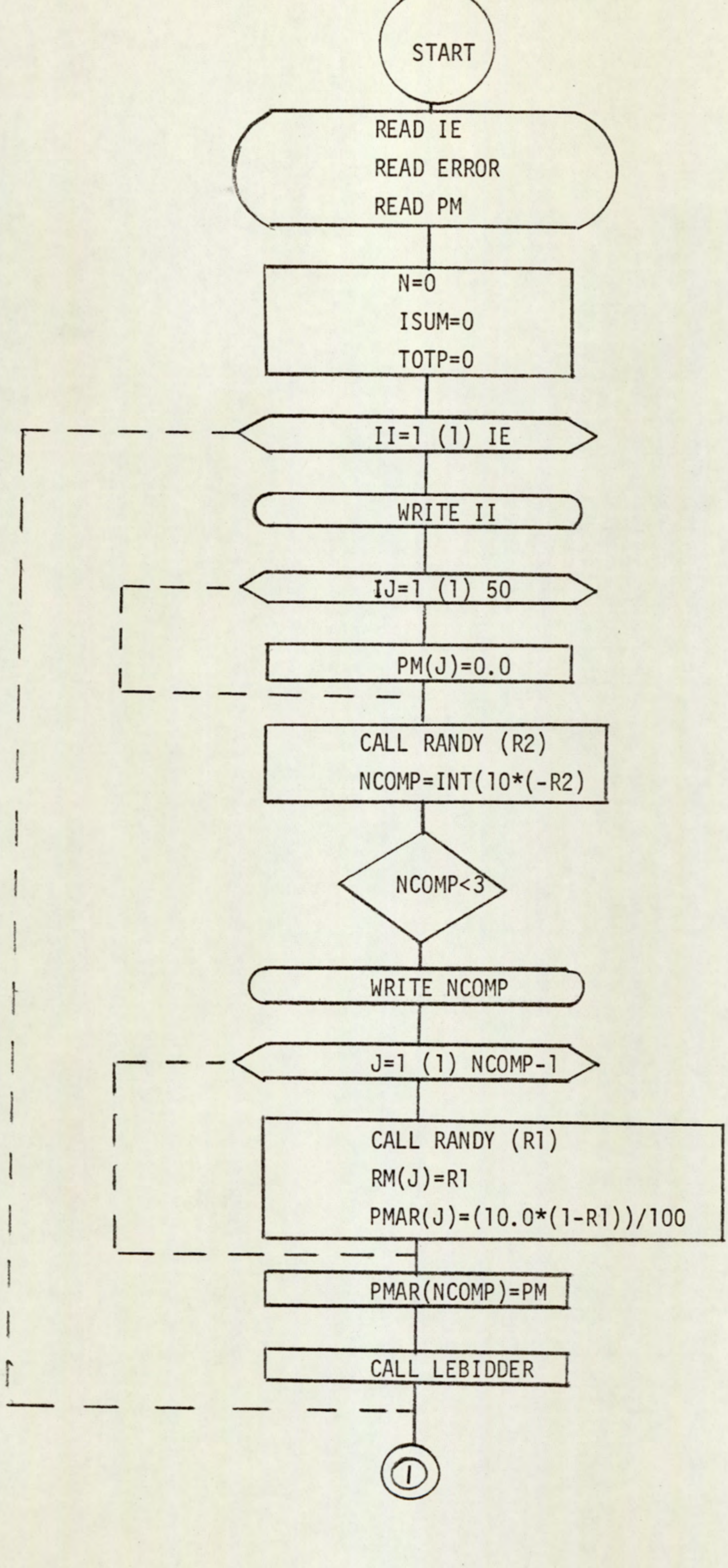
7.2.6 The simulation program sampling the number of competitors and their mark-up

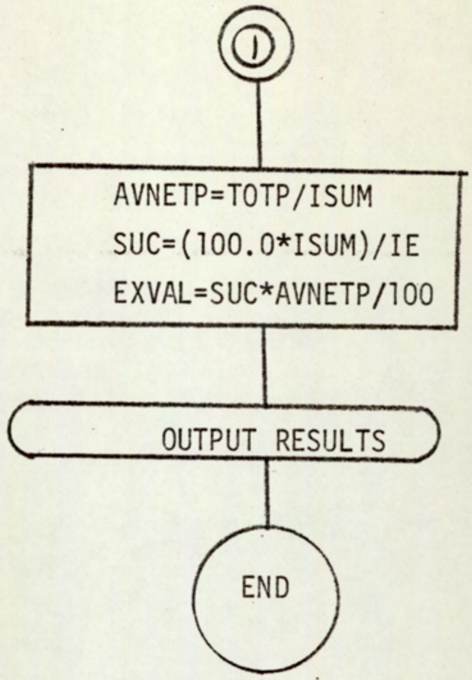
The estimation accuracy is sampled from a uniform distribution, therefore procedure LEBIDDER is similar to that of section (7.2.3)A.

The steps of the master segment are as follows:

1) The number of simulations, the estimation accuracy, and the mark-up of the last contractor M(US) are read.
2) An integer to initialize subroutine RANDY, the number of contracts won and the total profit of the last contractor are initialized.
3) A loop around the number of simulations is constructed.
4) Array RM, which stores the PRN's for sampling the estimation accuracy, is initialized.
5) Subroutine RANDY is called and the number of contractors sampled from a discrete distribution. If the number of contractors is less than 3 then a new PRN is generated and the sampling is repeated.
6) A loop around the number of competitors (number of contractors - 1) is constructed and their mark-ups are sampled from a continuous distribution by generating PRNs from subroutine RANDY.
7) Subroutine LEBIDDER is called to find the winning contractor.
8) The average net profit, success ratio, and expected value of the last contractor are evaluated.
9) The results are outputed.

Following is the flow chart of the master segment:


START
READ IE
READ ERROR
READ PM
N=0
ISUM=0
TOTP=0
II=1 (1) IE
WRITE II
IJ=1 (1) 50
PM(J)=0.0
CALL RANDY (R2)
NCOMP=INT(10*(-R2)
NCOMP<3
WRITE NCOMP
J=1 (1) NCOMP-1
CALL RANDY (R1)
RM(J)=R1
PMAR(J)=(10.0*(1-R1))/100
PMAR(NCOMP)=PM
CALL LEBIDDER
1


J
AVNETP=TOTP/ISUM
SUC=(100.0*ISUM)/IE
EXVAL=SUC*AVNETP/100
OUTPUT RESULTS
END

```
      MASTER SIM
      DIMENSION PMAR(50),ESTER(50),RM(30)
      COMMON N,PMAR,ISUM,TOTP,ESTER,NCOMP,RM,II,ERROR
      READ(1,90) IE
      READ(1,91) ERROR
      READ(1,92) PM
      N=0
      ISUM=0
      TOTP=0.0
      DO 6 II=1,IE
      WRITE(2,3) II
      DO 36 IJ=1,50
36    RM(IJ)=0.0
 1    CALL RANDY(R2)
      NCOMP=INT(10*(1-R2))
      IF(NCOMP.LT.3) GOTO 1
      WRITE(2,5) NCOMP
      DO 4 J=1,NCOMP-1
      CALL RANDY(R1)
      RM(J)=R1
4     PMAR(J)=(10.0*(1-R1))/100
      PMAR(NCOMP)=PM
      EXTERNAL RANDY
      CALL LERIDDER(RANDY)
 6    CONTINUE
      AVNETP=TOTP/ISUM
      SUC=(100.0*ISUM)/IE
      EXVAL=SUC*AVNETP
      WRITE(2,9)SUC
      WRITE(2,16)AVNETP
      WRITE(2,40)EXVAL
90    FORMAT(I4)
91    FORMAT(F10.3)
92    FORMAT(F10.3)
3     FORMAT(16H CONTRACT NO. = ,I3,/)
5     FORMAT(25H SELECTED NO. OF COMP. = ,I2,///)
9     FORMAT(20H ESUCCESS PERCENT = ,F10.3,/)
16    FORMAT(22H AVERAGE NET PROFIT = ,F10.3,/)
40    FORMAT(18H EXPECTED VALUE = ,F10.3,//)
      STOP
      END
      SUBROUTINE RANDY(RANDO)
      COMMON N
      INTEGER FACTOR
      N=N+1
      IF(N.GT.1) GOTO 10
      RNEXT=1023.0
10    RLAST=RNEXT
      NUM1=2**18
      K=83
      PRODUCT=K*RLAST
      FACTOR=INT(PRODUCT/NUM1)
      RNEXT=PRODUCT-FLOAT(FACTOR)*FLOAT(NUM1)
      RANDO=RNEXT/NUM1
      RETURN
      END
```

```
      SUBROUTINE LEBIDDER(RANDY)
      DIMENSION PC(50),TEND(50),ACHP(50),ESTER(50),PMAR(50),RM(5
      COMMON N,PMAR,ISUM,TOTP,ESTER,NCOMP,RM,II,ERROR
      DO 12 J=1,NCOMP
      ESTER(J)=ERROR
      CALL RANDY(R3)
      A=R3
      PC(J)=100*(((A-0.5)/0.5)*ESTER(J))
      TEND(J)=PC(J)*(1+PMAR(J))
      ACHP(J)=TEND(J)-100
      IF(J.GT.1) GOTO 32
      WRITE(2,30)
 32   WRITE(2,33)J,RM(J),PMAR(J),A,PC(J),TEND(J)
 12   CONTINUE
      IS=1
      DO 20 I=2,NCOMP
      IF(TEND(IS)-TEND(I))21,22,22
 21   IL=IS
      GOTO 20
 22   IS=I
      IL=I
 20   CONTINUE
      IF(IL.LT.NCOMP) GOTO 11
      ISUM=ISUM+1
      TOTP=TOTP+ACHP(IL)
 11   CONTINUE
 30   FORMAT(49H B.NR  RN1  MARK UP  RN2   PRIME CUST  TENDER VAL)
 33   FORMAT(I4,F7.3,F7.3,F7.3,F10.5,F13.5)
      RETURN
      END
      FINISH
```

7.3 Bidding data sets

7.3.1 Firm A data set

Tender No.	Date	Winning Tender figure	Firm 'A' Tender figure	Gross Profit %	Net Profit %	Nominal Cost	No. of Competitors
1	27.2.67	182,455	208,127	(10)	(5)	197,500	8
2	28.2.67	504,000	504,000	12.4	7.4	466,000	10
3	28.2.67	30,347	44,168	13.0	8.0	40,600	20
4	15.3.67	57,405	83,839	(10)	(5)	79,500	7
5	11.4.67	500,000	687,888	9.4	4.4	657,000	6
6	14.4.67	356,892	393,750	6.6	1.6	387,000	9
7	10.5.67	34,800	34,800	10.0	5.0	33,100	7
8	1.5.67	83,000	109,780	7.4	2.4	107,000	20
9	19.6.67	430,000	603,147	14.1	9.1	553,000	9
10	19.6.67	69,000	79,790	8.1	3.1	67,500	10
11	5.7.67	141,596	169,750	7.2	2.2	166,000	9
12	3.5.67	254,644	284,350	9.6	4.6	272,000	8
13	31.7.67	1,800,000	1,840,000	(10)	(5)	1,745,000	12
14	17.8.67	87,085	87,085	10.4	5.4	82,600	10
15	10.8.67	488,000	488,000	12.9	7.9	454,000	7
16	23.8.67	511,000	515,648	6.7	1.7	506,000	6
17	6.9.67	71,224	78,000	(10)	(5)	74,000	8
18	25.9.67	398,511	398,511	9.3	4.3	382,000	6
19	25.10.67	1,278,500	1,278,500	6.7	1.7	1,255,000	5
20	16.10.67	187,286	188,200	5.0	0	188,200	8
21	29.11.67	719,496	855,800	7.0	2.0	840,000	12
22	25.10.67	16,828	18,037	(10)	(5)	17,100	5
23	1.1.68	788,204	944,522	9.9	4.9	900,000	5
24	22.11.67	279,222	299,670	10.1	5.1	286,000	9
25	10.1.68	608,723	650,556	8.0	3.0	631,000	12
26	22.1.68	283,675	377,280	11.4	6.4	354,000	8
27	8.1.68	200,000	270,000	(10)	(5)	256,000	6
28	22.1.68	106,821	138,325	(10)	(5)	131,000	6
29	4.3.68	485,000	494,050	9.9	4.9	471,000	8
30	11.3.68	536,515	547,750	(10)	(5)	520,000	8
31	6.3.68	338,600	338,600	(10)	(5)	321,000	6
32	6.3.68	234,519	249,900	10.8	5.8	235,000	10
33	15.3.68	25,584	29,000	(10)	(5)	27,600	6
34	1.4.68	47,000	87,380	(10)	(5)	83,000	11
35	3.4.68	162,000	184,800	(10)	(5)	176,000	18
36	1.5.68	1,930,261	1,930,261	9.3	4.3	1,850,000	7
37	24.4.68	22,692	22,692	9.6	4.6	21,700	8
38	15.5.68	380,094	411,727	7.6	2.6	400,000	8
39	14.4.68	67,051	119,175	9.5	4.5	114,000	12
40	20.5.68	275,000	325,290	12.9	7.9	301,000	8
41	24.5.68	78,000	124,425	(10)	(5)	118,500	39
42	20.5.68	17,856	20,680	12.0	7.0	19,300	5
43	14.6.68	263,800	263,900	10.4	5.4	250,000	9
44	6.8.68	460,000	509,428	10.3	5.3	483,000	7
45	6.8.68	180,000	222,000	0.1	4.1	213,000	7
46	4.8.68	124,000	144,300	(10)	(5)	130,000	22
47	18.9.68	3,750,000	3,946,000	10.0	5.0	3,760,000	6
48	28.8.68	264,575	264,575	6.0	1.0	266,000	6
49	29.8.68	436,022	531,692	10.1	5.1	505,000	14
50	11.9.68	5,213	11,213	(10)	(5)	10,650	6

CONT"D

Tender No.	Date	Winning Tender figure	Firm'A' Tender figure	Gross Profit %	Net Profit %	Nominal Cost	No. of Competitors
51	28.11.68	1,480,000	1,509,900	8.3	3.3	1,460,000	8
52	4.11.68	216,000	234,500	8.0	3.0	227,000	5
53	25.11.68	1,058,000	1,058,000	9.0	4.0	1,018,000	6
54	4.11.68	380,000	694,840	8.9	3.9	668,000	9
55	9.12.68	160,000	235,935	2.3	4.3	226,000	8
56	14.1.69	268,000	464,600	7.8	2.8	450,000	9
57	10.1.69	20,695	27,400	10.2	5.2	26,000	12
58	22.1.69	30,701	42,500	12.0	7.0	39,700	14
59	22.1.69	135,104	157,000	9.3	4.3	150,000	18
60	12.2.69	618,000	618,000	12.3	7.3	576,000	6
61	10.2.69	433,652	450,600	7.3	2.3	441,000	6
62	12.2.69	95,986	125,875	5.7	0.7	125,000	7
63	25.3.69	317,000	411,400	7.7	2.7	400,000	6
64	28.3.69	60,958	81,900	7.7	2.7	79,700	10
65	10.4.69	314,000	325,860	7.4	2.4	318,000	7
66	29.4.69	403,434	479,300	7.8	2.8	466,000	15
67	11.4.69	222,000	306,530	8.2	3.2	297,000	6
68	9.4.69	66,000	80,850	7.6	2.6	78,700	12
69	10.4.69	31,900	31,906	12.6	7.6	29,600	5
70	28.4.69	795,000	838,300	9.6	4.6	800,000	6
71	2.5.69	121,220	121,226	7.7	2.7	118,000	8
72	15.5.69	104,128	114,800	9.4	4.4	110,000	8
73	28.3.69	79,700	111,000	8.4	3.4	107,400	18
74	9.6.69	94,860	160,000	8.5	3.5	154,000	18
75	9.6.69	229,365	287,700	6.8	1.8	283,000	6
76	8.7.69	151,915	151,915	6.6	1.6	149,000	6

7.3.2 Firm B data set

Tender No.	Date	Tenders figure	
1	December 1968	5,879,913	
		6,069,464	
		6,696,729	B
		8,740,694	
2	February 1969	3,142,189	
		3,530,646	
		3,550,441	
		3,717,603	
		3,978,280	B
		4,552,692	
3		1,379,640	
		1,437,529	
		1,480,301	
		1,501,344	
		1,587,684	B
		1,611,572	
		1,615,340	
4		6,942,790	
		7,701,606	
		8,496,400	B
		8,803,060	
		8,900,002	
		9,382,239	
5	March 1969	8,992,354	
		9,453,821	
		9,594,112	B
		10,346,022	
		10,437,083	
		10,521,001	
6		3,572,925	
		3,900,069	
		4,216,232	
		4,252,828	
		4,426,138	B
		4,523,966	
7	March 1969	3,283,858	
		3,581,937	
		3,668,264	
		3,728,727	B
		3,744,651	
		3,915,248	
8		9,918,163	
		10,181,753	B
		10,416,735	
		10,603,000	
		11,414,819	

Tender No.	Date	Tenders figures	
9	June 1969	3,098,937	
		3,337,039	B
		3,779,345	
		3,842,488	
		3,966,504	
10		9,760,110	
		10,210,122	B
		10,220,799	
		10,424,448	
		10,472,968	
		11,921,362	
11	July 1969	2,653,798	
		2,805,983	B
		2,847,445	
		2,853,028	
		3,200,147	
		3,264,350	
12		6,727,920	
		6,902,772	
		7,248,049	
		7,273,864	B
		7,338,754	
		7,508,054	
		7,804,994	
13		1,648,106	
		1,784,481	
		1,795,706	
		1,860,402	B
		1,912,647	
14		92,688	
		95,157	
		106,718	
		120,263	
		129,347	B
15		5,852,795	
		5,866,900	
		6,165,723	
		6,209,478	
		6,290,036	B
		7,004,430	
16	October 1969	1,629,851	
		1,707,286	
		1,708,483	
		1,787,523	
		1,792,472	B
		2,293,809	

Tender No.	Date	Tenders figures	
17		385,249	
		438,988	B
		443,696	
		505,653	
		515,665	
		525,882	
18		4,538,757	
		4,801,104	
		5,159,823	
		5,172,316	B
		5,307,731	
19		5,606	
		9,990	
		12,525	
		13,918	
		14,091	B
20	November 1969	8,054,614	
		8,534,680	
		8,953,647	
		9,072,082	B
		9,469,862	
		9,741,376	
		9,776,689	
21		1,923,745	B
		2,069,571	
		2,025,992	
		2,096,189	
		2,119,168	
		2,284,678	
		2,324,655	
22		5,598,383	
		6,262,030	
		6,262,760	B
		6,331,573	
		6,484,996	
		6,948,152	
23		148,803	
		162,325	
		176,054	
		194,021	
		200,981	B
		222,288	
24		1,608,918	
		1,721,260	
		1,763,077	
		1,826,810	
		1,842,471	
		1,868,450	B

Tender No.	Date	Tenders figures	
25		4,437,801	
		4,642,603	B
		4,704,745	
		6,021,738	
26		10,487,060	
		10,908,741	
		12,504,013	B
		12,567,168	
		13,381,259	
		15,443,850	
27	January 1970	454,049	
		456,422	B
		510,582	
		579,669	
		637,367	
28		278,702	
		289,664	
		302,922	
		305,775	
		315,075	
		315,578	
		390,295	B
29		1,033,551	
		1,103,595	
		1,117,995	
		1,268,280	B
		1,332,244	
30		1,979,101	
		2,105,423	
		2,122,178	
		2,133,244	
		2,211,740	B
		2,285,203	
31		431,726	
		474,350	
		503,677	
		507,500	
		510,879	
		525,545	B
		526,758	
32		563,131	
		567,404	B
		623,301	
		641,952	
		680,059	

Tender No.	Date	Tenders figures	
33		155,663	
		157,800	
		158,232	
		160,024	
		168,897	
		189,583	B
34		7,589,020	
		7,947,463	
		8,000,371	
		8,548,849	
		9,148,925	
		9,695,029	B
35		10,124,618	
		10,549,654	
		10,663,318	
		10,931,316	
		12,621,260	B
36		250,052	
		326,780	B
		340,341	
		371,732	
		389,696	
		401,010	
37		4,390,841	
		4,405,901	
		4,808,318	
		4,996,166	B
		5,095,383	
38		575,404	
		605,607	
		656,515	B
		708,366	
		725,321	
		748,959	
39		4,259,806	
		4,276,202	
		4,567,028	B
		4,667,175	
		5,247,922	
40		2,174,384	
		2,252,771	
		2,255,325	
		2,333,749	
		2,443,611	
		2,464,971	
		2,555,790	B

Tender No.	Date	Tenders figures	
41		3,575,755	
		3,608,510	
		3,681,463	
		3,760,533	B
		3,932,774	
		4,147,900	
42		15,826	
		20,705	
		23,001	
		27,777	
		29,852	B
		30,467	
		31,454	
		33,710	
43		642,814	B
		694,046	
		739,850	
		756,352	
		769,831	
		945,224	
44		2,080,629	
		2,134,051	
		2,218,643	
		2,253,064	
		2,300,467	B
		2,560,285	
45		3,782,825	
		3,988,917	B
		4,147,656	
		4,178,491	
		4,379,336	
		4,413,506	
		4,553,482	
46		1,361,029	
		1,455,653	
		1,460,319	
		1,574,157	
		1,596,366	B
		1,948,726	
47		9,721,973	
		9,998,494	
		10,255,053	
		10,437,998	
		10,992,971	B
		11,313,685	

REFERENCES

1. Bathurst, P.E., and Butler, D.A., "Building cost control techniques and economics". Heinemann, 1973.
2. Chatfield, C. "Statistics for Technology". Chapman and Hall, 1975
3. White, D., William, D., and Norman, L. "Operational research techniques". Vol.2, Business Books, 1974.
4. Box, G.E.P., and Muller, M.E., "A note on the generation of Normal deviates". Ann.math.Statist., Vol.28, pp.610-611, 1958.
5. Mode, E.B., "Elements of probability and Statistics". Prentice-Hall, 1966.
6. Friedman, L. "A competitive bidding Strategy". Operations research, Vol.4, pp.104-112, 1956.
7. Gates, M. "Bidding strategies and probabilities". ASCE, Jor. of Const.Div., V.93, proc.paper 5159, pp.75-107,1967.
8. Whittaker, J.D. "A study of competitive bidding with particular reference to the construction industry". Ph.D.Thesis, The City University, 1971.
9. Morin, T.L., and Clough, R.H. "OPBID: competitive bidding strategy model". ASCE, Jor.of Const.Div., Vol.95, proc.paper 6690, pp.85-106, July 1969.
10. Rickwood, A.K., "An investigation into the tenability of bidding theory and techniques". M.Sc. Project Report, Loughborough University of Technology. 1972.
11. Benjamin, N.B., "Competitive bidding for building construction contracts". Tech.report No.106, Dept. of Civil Engineering, University of Stanford, Stanford, Calif., June 1969.

12. Von Neumann, J., and Morgenstern, O., "Theory of games and economic behaviour". John Wiley and Sons., 1944.

13. De. Neufvill, R., and Stafford, J.H. "System Analysis for engineers and managers". McGraw-Hill, 1974.

14. Willenbrock, J.H., "Utility function determination for bidding models". ASCE, Jor. of Const.Div., p.133, July 1973.

15. Park, W.R., "The strategy of contracting for profit". Prentice-Hall, 1966.

16. Neal, B.H., and Benjamin, A.M. "Competitive bidding: the probability of winning". ASCE, Jor.of Const.Div., Vol.98, pp.313-330, September 1972.

17. Christenson, C., "Strategic aspects of competitive bidding for corporate securities". Div. of research, Harvard University, 1965.

18. Casey, B.J., and Shaffer, L.R. "An evaluation of some competitive bid strategy models for contractors". Civil Eng.studies, Const. research series No.4, Univ. of Illinois, June 1964.

19. Grunyer, P.H., and Whittaker, J.D. "Managerial judgement in a competitive bidding model". Oper.research Q. vol.24, No.2, pp. 181-191, 1973.

20. Wade, R.L., and Harris, R.B. "LOMARK: A bidding strategy", ASCE, Jor. of Const.Div., pp.197-211, March 1976.

21. Hansmann, F., and Rivett, B.H.P. "Competitive bidding". Oper. research Q., vol.10, pp.49-55, 1959.

22. Rosenshine, M. "Bidding models resolution of a controversy", Management Decision, Vol.4, No.2, 1970.

23. Pim, J.C., "Competitive tendering and bidding strategy". National Builder, pp.541-545, Nov. 1974.

24. McCaffer, R., "The effect of different estimating accuracies". The Project Manager, Vol.1, pp.3-5, September 1976.

25. Churchman, C.W., Ackoff, R.L., and Arnoff, E.L., "Introduction to operations research". Wiley, 1957.

26. McCaffer, R., and Pettitt, A.N. "Bidding behaviour in project management". The Project Manager, Vol.1, pp.5-8, Sept.1976.

27. "Price Policies and Bidding Strategies". Unpublished report obtained from Bryant C. & Son Ltd.

28. Armstrong, K. "The development and appraisal of computerised estimating system". M.Sc. thesis, Loughborough University of Technology, 1972.

29. Neale, R.H., "The use of regression analysis as a contractors estimating tool". M.Sc. project report, Dept. of Civil Engineering, Loughborough University of Technology, 1973.

30. Fine, B., "A brief explanation of bidding processes". Richard Costain report No.IN 16/71, Unpublished, Oct.1971.

31. Tocher, K.D. "The art of simulation", English University Press,1963.

32. Moulsdale, N.R. "PRN theory and its application to a reactor shielding problem". Dept. of Math. report, University of Aston in Birmingham, February 1970.

33. Puckdee, P., "Some experimental evidence for the existence of the Khintchine distribution". M.Sc. report, Dept. of Math., University of Aston in Birmingham, September 1971.

34. Meyer, P.L.,"Introductory Probability and Statistical Applications". Addison-Wesely, London, 1965.