

ESTIMATION OF MANPOWER FORECAST VARIATION BY GPSS SIMULATION

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INTRODUCTION

Traditionally, manpower estimation has been done on an expected value basis. Such estimates, although providing an estimate of the mean of manpower requirements, provide no indication of the probable spread about the mean. Manpower solution plans, however, often implicitly assume an estimate spread based upon experience gained from previous projects. This paper is concerned with estimation of manpower forecast variations, both in the aggregate and by skill level.

BASIC PROCESS MODEL

Consider the following basic model of a process. Figure 1 is a flow diagram for the process possessing the following characteristics:

1. There are at least n primary operations (OP1, OP2, . . . OPn) performed on each unit passing through the process.
2. There are $n!$ possible rework operations (R11, R12, . . . Rnn) on each unit passing through the process.
3. There are n primary yield points (S1, S2, . . . Sn) in the process.

Each primary and secondary operation on a unit represents a demand for manpower with a particular skill. Each yield point represents a possible reduction in "throughput" which affects the manpower requirement as well. Typically, primary operation times, rework times and yield rates are stochastic variables. Therefore, to effectively estimate manpower variation, process simulation must be based on a probabilistic specification of these process elements.

SUBJECTIVE DENSITY FUNCTION SPECIFICATION

Unfortunately, process information rarely is detailed sufficiently to permit direct specification of the density functions of stochastic variables. When such information is available, the developed cumulative distribution function can serve as input to a General Purpose Simulation System (GPSS) model in the form of a tabled function. When such information is not available - and it often is not - subjective estimation can serve as a basis for specification of a density function.

Figure 2 illustrates a family of 81 curves developed by the writer to serve as normalized density functions for specification of stochastic variables. Selection of a particular density function from the family is based on

answers to five questions concerning the variable of interest. The individual most familiar with the process is asked to estimate:

1. The modal value (most likely). Point X
2. The lower limit (the value below which only 5 per cent occurrence is expected). Point Y
3. The upper limit (the value above which only 5 per cent occurrence is expected). Point Z
4. The lower limit end point condition (a subjective selection of one of three curves of varying flatness as the curve passes through point Y).
5. The upper limit end point condition [similar to (4) for point Z].

These five questions are in an increasing order of difficulty of obtaining accurate information. The information they extract is believed sufficient, for most applications to allow specification of a density function which approximates the shape of the underlying density function for the variable of interest. The 81 curves represent a family possessing three shapes (i.e., kurtosis levels) at both ends of the density function, at five possible left or right skewness levels. The ratio of XZ to YZ permits selection of the appropriate skewness level. A Fortran program was developed to produce X-Y coordinates for the 81 cumulative distribution functions in the GPSS specified format.

Figure 3 illustrates the use of the family of density functions.

Assume the most likely (i.e., modal) time required for an operation is estimated at 70 minutes. Fifty minutes is estimated as the lower limit below which operation times occur 5 per cent of the time. Similarly, 100 minutes is estimated to be the 5 per cent upper limit. Since operating times very rarely take less than 47 minutes, a type C curve is selected for the left half of the density function. Because times extend occasionally as high as 125 minutes, a type A curve is chosen for the right half of the density function.

The ratio of XZ to YZ of $30/50 = 0.6$ comes closest to a number 2 skewness level which has a ratio of 0.625. Therefore, a CA2 curve is employed. The simulation generates operation times distributed according to density function CA2 employing lower and upper 5 per cent limits of 50 and 100 minutes, respectively. Similar specification of stochastic variables for the other operation times, rework times and per cent transfers to rework or scrap will complete specification of stochastic elements of a model.

SUMMARY

To generate the desired output, which is a distribution of labor requirements by specified skills, a GPSS model is developed for each specific process. Figure 4 is a GPSS model for a process containing three primary and five secondary operations. The model generates operation times, rework times, and transfers to rework and scrap for successive transactions based on the function values produced employing the selected cumulative distribution functions. Data cards for all 81 curves were produced by a FORTRAN program. The data cards for

curves AA1 and CA3 were merely inserted into the above GPSS program. Figure 5 is a distribution of labor times accumulated for a single run of 100 units through the process. An obvious extension of the model to permit estimation of interference times would be to allow units to queue at process steps as a function of facility restrictions. Such a model would permit estimation of the labor skills required and their variation for a given level of "throughput", including facility restriction effects, for a defined calendar period.

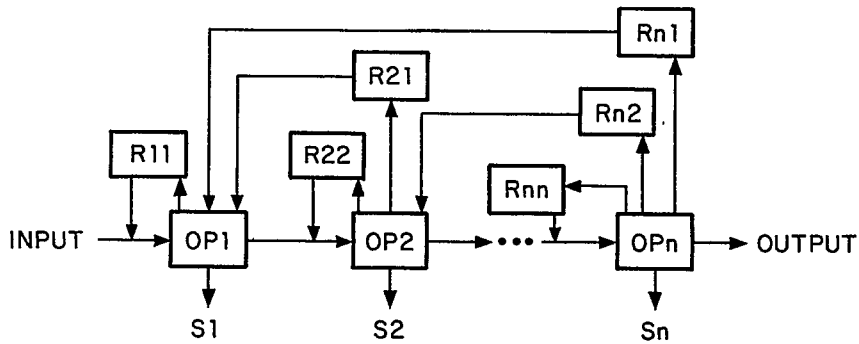


Figure 1. Basic Process Model

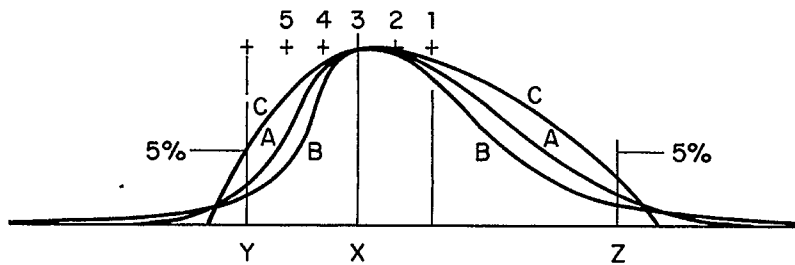


Figure 2. A Family of Density Functions

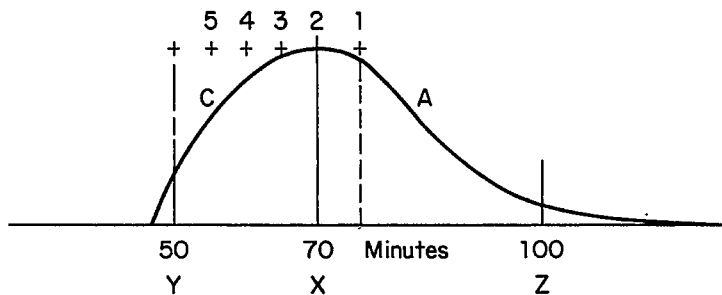
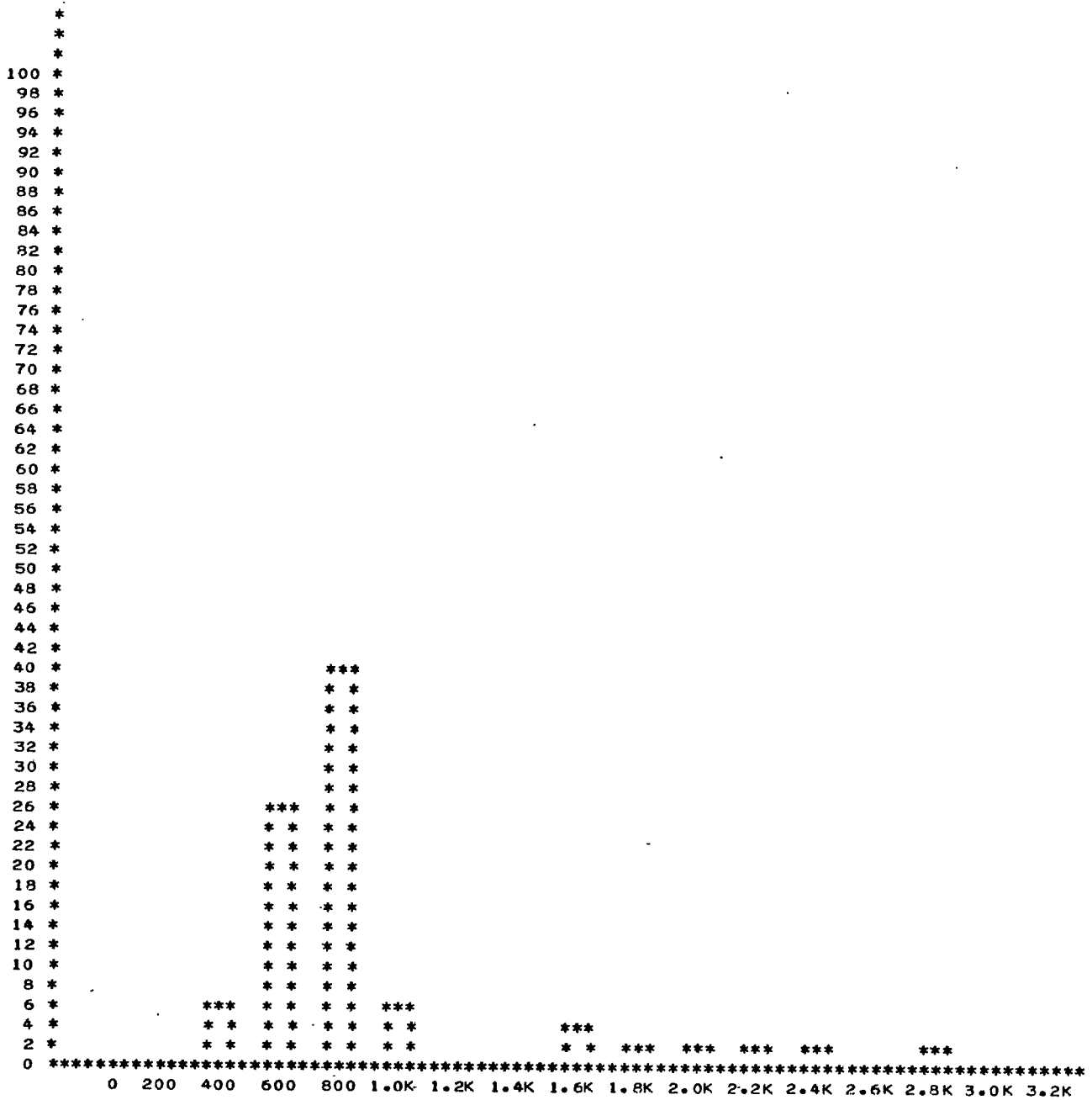


Figure 3. Distribution of Operation Times



SKILL 1 MANPOWER DENSITY FUNCTION ESTIMATE

Fig. 5