Using Multi-logistic Distribution and Stochastic Goal Programming for Estimating the Human Resources for Development Strategy.

Abstract

The main goal of this paper is to anticipate the expected estimates of the human resources to build up a development strategy of employment. Three methodological approaches were used to achieve this goal, the logistic distribution, Bayesian technique and the stochastic goal programming (SGP).The multi-logistic regression (MLR) model was used to analyze the relationship between a multi-categorical outcome of human capital and their human resources. Using the SGP approach, the MLR solution gave percentages of correct allocations for the human resources among the human variables as well as it provided the optimal estimates for the parameters of the model. An alternative and richer MLR with matched case- control outcomes model was built for each of the human force categories applying the Bayesian approach to construct the matched model and applying the SGP solution gave more information about the parameters 'estimates of the MLR model. Finally a SGP model was constructed, inversely, to project the human resources categories satisfying the development goals of labor productivity for the planned output pattern.

1.Introduction

The paper intended to introduce a specified structure of the employment categories through an optimal estimation of the future requirements for manpower resources. The design would involve a comprehensive analysis of the present situation of the high level human resources based on assessment of both occupation and education system. In this work the logistic distribution with multinomial categories is used in a stochastic goal programming (SGP) model[1] to represent the relationship between the human capital categories and their resources. Such a task was carried out by estimating the probabilities of the correct classification of human capital among 4 categories, namely the stock of human capital, the net additions to this stock, the higher level education orientation share and "others".

Though the strategic human capital plan as "Parnes" assumption [10] ,is meant by the of labor development of the higher level labor but we included here the low level labor as a fourth category of human capital ,as coded "others" , to improve its share through the combined stochastic estimation of all of the human resources.

However the optimal allocation of these categories would be obtained by fitting the multinomial logistic regression (MLR) distribution [3] with 4 responses to a set of 13 independent quantitative variables representing the human resources indicators. The SGP solution of this model would give optimal estimates for the MLR parameters. Then by constructing a SGP model[16] once more with the inverted MLR solution, we could get optimal estimation for the labor resources.

The plan of the paper is ordered as follows: section 2 presents briefly, the relation between the human capital and their resources explaining the necessity for building a strategic model of employment development. The mathematical representation of this policy model will be dealt with in subsection 2.1. Subsection 2.2 concerns building the SGP model and its theoretical solution method. Section 3 gives an alternative and richer optimal allocation model based on the matched probabilities of the human capital categories. Section 4 presents the adjoint SGP solution of the matched model. Section 5 provides the MLR model for the best allocation of human capital categories .While Section 6 provides the SGP method of estimating the human resources elements using the inverted probabilities of the MLR model.

2. Optimal Estimation Design for the Human Resources:

Two main problems of human resources development, one is the shortage of high level manpower with critical skills. Second is related to underutilization of manpower. However the human resources planning must be concerned both with building knowledge and skills and providing employment and broader opportunity for unutilized and underutilized manpower [10]. Therefore it is necessary to consider the high level manpower in view of both occupations and educational level. On the other hand the overabundance of unskilled and untrained manpower would cause spread out of underemployment and disguised unemployment, while the supply of unemployment intellectuals will cause a surplus of unutilized human capital. Therefore the planner must identify the causes of manpower surpluses and consider the related factors as population growth, limited employment capacity of modern industry and others.

In order to build up the strategies of human capital or high-level manpower development for the two processes of generation and utilization ,the planner should hence look for an appropriate education system depending on primary ,secondary and higher education level as well as on the available choices of the requirements for teachers who providing it. Usually the system must be limited by economic, political and social imperatives and other several matters out of planner control. However in accordance with the international definition and classification of occupational and educational categories of the high-level manpower, we have identified four aggregated occupations to be used as a measure of the present situation of human capital and have chosen 13 human resource indicators for assessment of their requirements through the logistic regression model as will be analyzed afterwards.

2.1 Multi-Logistic Regression (MLR) Model for Best Allocation of Human capital Categories:

In relation of occupations to formal educational requirements we attempted to introduce best assessment for the correct classification of the human capital , as divided by Parnes[10] into 3 parts, human stock ,additions to manpower stock and the incentives of higher level labor. Accordingly we defined 13 statistical indicators for measuring their human resources. The first seven are chosen from among the identified international and Egyptian classification of occupations to partially measure the stock of high and low level manpower [3]. The next four are chosen from the education system to measure the additions to the stock, which measure the rate of human capital formation over a certain period, and the last two, indicate the higher level manpower orientation.

However for building the best strategy of human capital development we started with fitting MLR model[9],Y=f(X),with four outcomes y_j,j= 0,1,2,3,representing the probability of whether or not the individual falls in one occupation of these four manpower categories .On the other side we chose 13 indicators of the human resources as independent variables ,X, in the model as defined below.

2.1.1 Notations:

Y: is a 4- category vector of the dependent outcomes variable y_j ,j=0,1,2,3.

Where:

y_0*:is the probability that the individual falls in low level occupations as coded* "others".*They represent those people who are deemed to be noneducated and not included in preceding categories.*

y_1*:is the probability that the individual falls in the stock of the high level manpower category*

y_2*:is the probability that the individual falls in the additions to stock .*

y_3*:is the probability that the individual falls in the higher level eduction opportunity.*

X : is R vector of the independent variables, x_r , r=0,1, ...,R, R =13 and x_o=1,where the 13 variables are defined as follows:

x_1 : is the no. of teachers in primary and secondary schools per 100,000 population.

x_2 : is the no. of managers ,legislators and seniors officials per 100,000 population.

x_3 : is the no. of professionals, engineers, scientists, dentists and physicians per 100,000 population.

x_4 : is the no. of sub-professionals group, including engineering, technicians, nurses, medical assistant and the skilled workers, per 100,000 population.

The x_1, x_2 ,x_3 ,x_4 , indicators are assumed to be partial measure of the high labor inventory as coded by the first outcome, y_1, of the MLR model.

x_5 : no. of services, crafts and plant workers per 100,000 population.

x_6 : no. of skilled agricultural workers per 100,000 population.

x_7 : no. of workers in elementary jobs per 100,000 population.

The variables x_5 ,x_6 ,x_7 are very useful measure contributing the "others" category of manpower as denoted by the outcome y_0 .

x_8 : Pupils enrolled at the 1st level (elementary and primary) of education as a percentage of the estimated population aged 5-14.

x_9 : Pupils enrolled at the 2nd (secondary) level of education as a percentage of the estimated population aged 15-19.

x_{10} : Pupils enrolled at the 1st and the 2nd level in the technical and commercial education as a percentage of the estimated population aged 15-19.

x_{11} : Pupils enrolled at the 3rd (higher) level of education as a percentage of the estimated population aged 20-24.

The four variables x_8 to x_{11} are considered to contribute to the net additions to the labor stock as measured by educational attainment .They actually express the rate of accumulation of human capitals as denoted by y_2.

x_{12} : The percentage of graduates in scientific and technical faculties in recent years.

x_{13} : The percentage of graduates in faculties of humanities, fine arts and law in recent years.

The two variables x_{12} ,x_{13} are considered as indicators of labor improvement and conform the orientations of higher educated labor.

x_{tr}: is the t^{th} observation of the r^{th} variable ,t=1,2,...,n, n is the number of observations , r=0,1, ...,R.

2.1.2 The Model:

The MLR model was adequately chosen to represent the relationship between the labor force (Y) as a dependent variable with 4 outcomes , y_j ,j=0,1,2,3, and the human resources X as a set of R=13 independent variables x_r, r=0,1,...,13 , x_0=1 , usually called covariates. The probability density function, (pdf) , f(X) of the MLR distribution may be a reasonable model to describe the relation i.e., f(X,Y) and would give the correct allocations for the outcomes.

If the conditional probability density function of outcome y_j given X, is denoted by:

$$f_j(X)= pr(y=j|x)=p(y_j) \qquad ,j=0,1,2,3 \qquad (2.1)$$

Then the pdf of the MLR model will have the following general form:

$$p(y_j) = pr(y=j|x) = \frac{e^{\acute{\beta}_j x}}{\sum_{j=0}^{3} e^{\acute{\beta}_j x}} \quad ,j=0,1,2,3 \qquad (2.2)$$

The four conditional probabilities $p(y_j)$'s of the outcome categories vector Y given the covariate vector X of length R with $x_0=1$ are binary variables ,b(0,1), each of which takes the value 1 at the case status and zero at the control status. However, the parameter vector β is of 3(R+1) elements, $\beta' = \beta_1', \beta_2', \beta_3'$ while the vector $\beta_0 = 0$ for y=0 will serve as a reference or control outcome value, then,

$$p(y_j) = \frac{e^{\acute{\beta}_j x}}{1+\sum_{j=1}^{3} e^{\acute{\beta}_j x}} \quad ,j=0,1,2,3 \qquad (2.3)$$

Expressing *the pdf of eq.* (2.2) *in terms of the logit functions* $g_j(x), j = 1,2,3$ where $g_j(x)$ *'s are determined* from the transformed form of the MLR function as:

$$g_j(x) = \ln\left(\frac{p(y=j|x)}{p(y=0|x)}\right) = \beta_{0j} + \beta_{1j}\, x_1 + \beta_{2j}\, x_2 + \cdots + \beta_{Rj}\, x_R = \acute{\beta}_j X,\ j = 1,2,3 \quad (2.4)$$

Then:

$$p(y_j) = \frac{e^{g_j(x)}}{\sum_{j=0}^{3} e^{g_j(x)}} \quad ,j=1,2,3 \qquad (2.5)$$

Since $\beta_0 = 0$ then $g_0(X)=0$ .That is we shall have only 3 logit functions because the binary outcome in the MLR model is given by y_j versus y_0 ,j=1,2,3 and y_0 is used as reference variable which may be chosen arbitrary according to the goal of the research .The conditional probabilities in (2.5) may be written for each observation t, t=1,2,...,n as follows:

$$pr(y=j|x_t) = \frac{e^{g_j(x_t)}}{1+\sum_{l=1}^{3} e^{g_j(x_t)}} \quad ,j=1,2,3 \qquad (2.6)$$

Where x_t is a R+1 vector of covariates $X_t = (X_{t0}, X_{t1}, \ldots, X_{tR})$,R=1,2,...,13

$\acute{\beta}_j = (\beta_{0j}\ \ \beta_{1j}, \ldots, \beta_{Rj})$,j=1,2,3

2.2 Constructing stochastic goal programming (SGP) Model:

Using the MLR model we shall construct a SGP system [5],[11]for estimating its parameters as follows:

Find β_j , j=1,2,3 so as to

Min $\sum_{t=1}^{n} \sum_{j=0}^{3} d_{tj}^{-} + d_{tj}^{+}$

s.t

$$y_{t0}=pr(y=0|x)=\frac{1}{1+\sum_{j=1}^{3} e^{\beta'_j x_t}} + d_{t0}^{-} - d_{t0}^{+}$$

$$y_{t1}=pr(y=1|x)=\frac{e^{\beta'_1 x_t}}{1+\sum_{j=1}^{3} e^{\beta'_j x_t}} + d_{t1}^{-} - d_{t1}^{+}$$

$$y_{t2}=pr(y=2|x)=\frac{e^{\beta'_2 x_t}}{1+\sum_{j=1}^{3} e^{\beta'_j x_t}} + d_{t2}^{-} - d_{t2}^{+}$$

$$y_{t3}=pr(y=3|x)=\frac{e^{\beta'_3 x_t}}{1+\sum_{j=1}^{3} e^{\beta'_j x_t}} + d_{t3}^{-} - d_{t3}^{+}$$

Where

$\beta_0 = 0,$

$d_{tj}^{-} * d_{tj}^{+} = 0$

$d_{tj}^{-} \geq 0\,,\ d_{tj}^{+} \geq 0,\ \ X_t \geq 0\ \ ,t=1,2,\ldots,n\ ,j = 1,2,3$

$\beta_j^{`} = (\beta_{0j}\ \ \beta_{1j}, \ldots, \beta_{Rj})\qquad ,j=1,2,3$

$x_t = (x_{t0}\ x_{t1} \ldots x_{t,13})\ ,\ \ x_{t0}=1\ \ \ ,t=1,2,\ldots,n$

$$\beta_j' x_t = \sum_{r=0}^{13} \beta_{jr} x_{tr} \qquad , x_{t0} = 1$$

"Gams" program may be used [1]to solve this model where the main goal is to get y_j as close as to one .The solution will give optimal estimates for labor resources parameters $\beta_1, \beta_2, \beta_3$ from which we can calculate the probabilities y_j ,j=0,1,2,3 .The model can be fitted to any set of data in time series of some period. They consist of n observations for each of the thirteen explanatory variables X. These must be combined in a certain order according to the case status of the binary variables y_j , j=0,1,2,3. That is if j=0 then y_0=1 and y_1= y_2= y_3=0. If j=1 then y_1=1,y_0= y_2= y_3=0 and so on. We are preparing an empirical application of this model at the near future period to attach and validate the model. As the required data of employment categories for economic sectors are available for Egyptian economy.

3. Modification of the MLR- pdf According to the case-Control Matched Design Sample.

From the preceding analysis of the relation between the human capital (Y) and the labor and educational resources(X) it seemed that the human resources covariates should be identified into 4 groups according to the requirements of each labor force outcome as we coded now by y_j , j=1,2,3,4.Thereso ,a modification to allow for replication at covariate patterns is required using cohort data technique in designing the covariate sample.The simplest design in fitting the MLR model is where the polytomous outcome variable must be fixed conditional on stratification of the determined human resources data . In this setting the probability of each category of the dependent variable is one case versus 3 zeros references. It means the polytomous logistic distribution must be applied with matched probabilities of the case –control responses, for each outcome ,based on cohort data. As we have 4 subjects represented by the 4 outcomes of the dependent response variables y_1, y_2 , y_3 , y_4 , the probability of occurring each one in this case will be met via three zero probabilities called references or controls status of the outcome [9]. It implies that each case status with probability 1 is matched to 3-control probabilities, which is known as the 1-3 case-control matched design analysis. Consequently we must assign to each one a certain set of human resources indicators, according to which the sample data would be stratified with each stratum has 4 subjects. However we could classify the 13 chosen resource indicators into 4 groups as now coded x_1 ,x_2 , x_3 ,x_4 , where the first group x_1 contains the first 4 indicators of observation t, x_{t1} ,x_{t2} , x_{x3} ,x_{t4} and is allocated to feed the first case- outcome as defined by stock category Y_1.Similary, the second group contains 3 indicators, x_{t5} , x_{t6} , x_{t7} and the third group contains the 4 indicators, x_{t8} , x_{t9} , $x_{t,10}$, $x_{t,11}$,while the fourth contains the last two $x_{t,12}$, $x_{t,13}$, each of these to produce the outcome categories y_2 , y_3 , y_4 ,as defined by "others", additions and higher orientation, respectively.

However since we have 4 outcomes each of which is matched to 3 controls (zero outcomes) we shall have a sample of T=4n size, and the polytomous logistic conditional probabilities must be obtained from the 4-3 matched logistic distribution. But we shall treat each case outcome individually using the 1-3 case- control matched analysis owing to the available software of the GAMS program as will be explained below.

4. Allocating the Human Resources to the Manpower Outcomes Using Stratified Sample Data.

The study is based on modeling a MLR distribution in which the values of the covariates (X) are fixed and the outcome is measured conditionally on the observations of these values and on the other hand the parameter estimators should be obtained when sampling is performed by stratification conditional on the outcome variables. Therefor the matched case –control likelihood function must be constructed to obtain the logistic regression probabilities using "Bayes" theory , where the dependent variable would be an outcome with binary status of 1-3 case-control probabilities. In this case the likelihood function is the product of the stratum - specific likelihood functions which depends on the probability that the subject was selected for the sample stratum, and the probability distribution of the covariates as given by:

$$\prod_{t=1}^{T} P(y_t, X_t|s=1) = \prod_{t=1}^{T} P(y_t|X_t, s=1)P(X_t|s=1) \qquad (4.1)$$

Which is equal by "Bayes" law to:

$$\prod_{t=1}^{T} P(X_t|y_t, s=1)P(y_t|s=1) \qquad (4.2)$$

Where the variable s denotes the selection (s=1), or non selection(s=0), of the subject.

If there are T strata each of which has 4 subjects with n_{1s} =n cases and n_{0s} =3n controls ,(s=1,2,...i,...,T),then the conditional likelihood for the s^{th} stratum is constructed as the probability of the observed data conditional on the total of the stratum and the total number of cases observed as shown below.

$$\ell_s(\beta)= \frac{\prod_{i=1}^{n_{1s}} P(X_i|y=1) \ \prod_{i=n_{1s}+1}^{4n} P(X_i|y=0)}{\sum_j \prod_{i_j}^{n_{1s}} P(x_{i_j}|y=1) \ \prod_{i_j=n_{1s+1}}^{4n} P\left(x_{i_j}\middle|y=0\right)} \qquad (4.3)$$

where

T =4n ,n_s=n_{1s}+n_{0s}

Eq.(4.3) explains the probability of the observed outcome relative to the probability of the data for all possible assignments of n_{1s} cases and n_{0s} controls to n_s=(n_{1s} + n_{0s}). It implies that there are $\binom{n_s}{n_{1s}}$ possible assignments; j denotes any one of these assignments with subscript i_j for the i^{th} observation and the j^{th} assignment. Applying "Bayes" theorem to each term in eq.(4.3) , the conditional probability distribution of the covariates which is known as the conditional likelihood function say $\iota_s^*\beta)$, can be derived for stratum s as follows:

$$\iota_s^*\beta) = P(X|Y,s=1) = \frac{P(Y|X,s=1)P(X|s=1)}{P(Y|s=1)} \qquad (4.4)$$

However the posterior probability in the first term of the numerator P(Ylx,s=1) of eq.(4.4) can be expressed as the product of the prior pdf ,p(Y|X) and the probability of choosing the stratum design variables. In the existence of 3 controls where we have 4 responses y_j's ,j=1,2,3,4, we shall have a matched probability of any subject y_j , say y_1 ,via $P(y_2)= P(y_3)= P(y_4)=0$ as we call them $f_2(x)$, $f_3(x)$ and $f_4(x)$ versus the case - probability $f_1(x)$. However By "Bayes" theorem [12] when y_1=1:

$$f_1(x_1)=P(y_1=1|x_1,s=1)=\frac{P(y_1=1\mid X_1)P(s=1|X_1,y_1=1)}{P(y_1=1|X_1)P(s=1|X_1,y_1=1)+\sum_{j=2}^{4}P(y_j=0|X_j)P(s=1|X_j,y_j=0)} \quad (4.5)$$

And when y_1=0, then:

$$[1-f_1(x_1)]=$$

$$P(y_1=0\mid x_1,s=1)=\frac{P(y_1=0\mid X_1)P(s=1|X_1,y_1=0)}{P(y_1=0|X_1)P(s=1|X_1,y_1=0)+\sum_{j=2}^{4}P(y_j=1|X_j)P(s=1|X_j,y_j=1)} \quad (4.6)$$

i.e, the conditional posterior pdf of y_1 is:

$$f^*_1(x_1)=p(y_1|\ x,s=1)=f_1(x_1)^{y_1}\,(1-f_1(x_1))^{1-y_1} \quad (4.7)$$

Similarly each of $f_j(x_j)$,j=2,3,4 is determined in a similar form as (4.5), (4.6)

Then the conditional likelihood function for a sample of size n of the stratified logistic with probability of occurring y_1=1 versus y_2= y_3= y_4=0,is:

$$P(y_1|X_t,s=1)=\prod_{t=1}^{n}f_1(X_{1t})^{y_{1t}}f_2(X_{2t})^{y_{2t}}\ f_3(X_{3t})^{y_{3t}}\,f_4(X_{4t})^{y_{4t}} \quad (4.8)$$

Substituting from (4.8) in (4.4) ,with writing P(X| s =1)= P(X) ,where the selection of cases and controls is assumed independent of the coveriates, yields the specific- stratum conditional likelihood function as:

$$l_s^*(\beta)=\prod_{t=1}^{n}f_1(x_{1t})^{y_{1t}}f_2(x_{2t})^{y_{2t}}\ f_3(x_{3t})^{y_{3t}}\,f_4(x_{4t})^{y_{4t}}\frac{P(X_t)}{P(y_{1t}|s=1)} \quad (4.9)$$

And from (4.9), the full conditional likelihood function will be the product of $l_s^*\beta)$ over the T strata.Noting that the modeling is not conceptual but computational so that the 1-3 binary variables are usually not constructed or used in the actual MLR analysis but are introduced to clarify the likelihood function. Thus:

$$L(\beta)=\prod_{s=1}^{T}l_s^*(\beta)=P(y_1\mid X,s=1)\prod_{s=1}^{T}\frac{P(X)}{P(y_{1s}|s=1)} \quad (4.10)$$

When setting any one of y_2, y_3 *or* y_4 *as a design variable it is possible to obtain*

their probabilities by the same steps of eq.(4.3) - eq.(4.10).

however in our case we have 4(n-1)+ R parameters consisting of the R slope coefficients for the covariates and (4n-4) coefficients for the stratum-specific design variables using 4n sample size.

Therefore the first term in the right of eq.(4.10) gives the likelihood obtained of "cohort" stratified case – control data with the outcome of interest as the dependent variable. The second term is the probability distribution of the covariates X, P(X) ,which is usually assumed to have no information about the coefficients β as it represents a sufficient statistic for the pdf of the stratum specific design variables. Thereso we shall regard the stratum specific parameters as nuisance parameters and neglect their estimators. The conditional likelihood obtained in (4.10) would then give consistent maximum likelihood estimators of the slope in the MLR model [9]

Now consider the MLR model and applying "Bayes" theorem in eq.(4.3) as explained above, the conditional likelihood $l_s(\beta)$ is:

$$l_s(\beta)=\frac{\prod_{i=1}^{n_{1s}} e^{\beta' x_i}}{\sum_j \prod_{i_j}^{n_{1s}} e^{\beta' x_i}} \qquad (4.11)$$

If the logit in the s[th] stratum is $g_s(X) = \delta_s + \beta' X$, where,

δ_s is the contribution to the logit of all terms constant within the stratum.

Then the coefficient vector β would contain only the R =13 slope coefficients,

$\beta' = \{\beta_{ij}, i=1,\dots,R, j=1,2,3,4\}$ .Therefore eq.(4.11) will depend only on β' for the constant term $\frac{e^{\delta_s}}{1+e^{\delta_s+\beta' X}}$ that appears in both the nominator and the dominator of eq.(4.11) cancel out.

Hence the general form of the full conditional likelihood is the product of $l_s(\beta)$ over the T strata and conditional maximum likelihood estimators for β is that value which maximizes eq.(4.11).

5. Optimal Parameters' Estimators of the Matched Design Employment Sample.

Consider a stratified sample design of 1-3 matched case –control status data and let the value of the covariates for the case in stratum s be denoted by x_{1s} , and the values for the three controls be denoted by x_{2s} , x_{3s} and x_{4s} .The probability of occurring the outcome y_1 versus the three zero status as indicated by the contribution to the likelihood for this stratum, eq(4.11) is obtained as follows:

$$P(y_1=1|X, y_2= y_3 =y_4=0)=\frac{e^{\beta_1' x_{1s}}}{e^{\beta_1' x_{1s}}+e^{\beta_2' x_{2s}}+e^{\beta_3' x_{3s}}+e^{\beta_4' x_{4s}}}$$

Then the probability of each outcome of that MLR model in each case is matched to 3j's controls must be obtained individually with a similar matched stratified design as has been followed to the results of the previous equation.

The SGP model can be created as follows:

Find $\beta` = \beta_1, \beta_2, \beta_3, \beta_4$ so as to:

Min. $\sum_{s=1}^{T}\sum_{j=1}^{4} d_{sj}^- + d_{sj}^+$

S.t.

$$P(y_1=1|X_s) = \frac{e^{\beta_1' x_{1s}}}{e^{\beta_1` x_{1s}} + e^{\beta_2` x_{2s}} + e^{\beta_3` x_{3s}} + e^{\beta_4` x_{4s}}} + d_{s1}^- - d_{s1}^+ ,$$

$$P(y_2=1|X_s) = \frac{e^{\beta_2' x_{2s}}}{e^{\beta_1` x_{1s}} + e^{\beta_2` x_{2s}} + e^{\beta_3` x_{3s}} + e^{\beta_4` x_{4s}}} + d_{s2}^- - d_{s2}^+ ,$$

$$P(y_3=1|X_s) = \frac{e^{\beta_3' x_{3s}}}{e^{\beta_1` x_{1s}} + e^{\beta_2` x_{2s}} + e^{\beta_3` x_{3s}} + e^{\beta_4` x_{4s}}} + d_{s3}^- - d_{s3}^+ ,$$

$$P(y_1=4|X_s) = \frac{e^{\beta_4' x_{4s}}}{e^{\beta_1` x_{1s}} + e^{\beta_2` x_{2s}} + e^{\beta_3` x_{3s}} + e^{\beta_4` x_{4s}}} + d_{s4}^- - d_{s4}^+ ,$$

Where:

$d_{sj}^- * d_{sj}^+ = 0$

$d_{sj}^- \geq 0$, $d_{sj}^+ \geq 0$, s=1,...,T ,j=1,...,4

$x_s \geq 0$,s=1,...,T.

6. Prediction of Human Resources Using SGP Model:

Recalling that the logistic regression for a binary outcome variable was parameterized in terms of the logit of $y_j=1$ versus $y_j=0$ where in case of four outcome model, we will have 3 logit functions $g_j(X)$, j=1,2,3.Then since the parameters`estimators as well as the exponential rates,$e^{\beta` X}$,*of achievement preference* cases could be estimated by fitting the MLR to the labor resources variables ,where:

$$g_j(X) = \ln \frac{p(y_j)}{p(y_0)} = \ln e^{\beta`_j X_j} \quad ,j=1,2,3,$$

and the logit estimates are:

$$\hat{g}_1(X) = \hat{\beta}_{0,1} + \hat{\beta}_{11}x_1 + \hat{\beta}_{21}x_2 + \hat{\beta}_{31}x_3 + \hat{\beta}_{41}x_4 \tag{6.1}$$

$$\hat{g}_2(X) = \hat{\beta}_{0,2} + \hat{\beta}_{82}x_1 + \hat{\beta}_{92}x_9 + \hat{\beta}_{10,2}x_{10} + \hat{\beta}_{11,2}x_{11} \tag{6.2}$$

$\hat{g}_3(X) = \hat{\beta}_{03} + \hat{\beta}_{12,3}\, x_{12} + \hat{\beta}_{13,3}\, x_{13}$ (6.3)

However the SGP model may be constructed to determine the anticipated values of the human resources, x_{ij}'s for a forecast year which satisfy the following sets of goals:

- ✓ First, the best allocation of human resources among the manpower categories so that the achievement preferences ratios are satisfied.
- ✓ Second, the highest possible achievement rate of allocations with probability greater than or equal α, say α =0.95.
- ✓ Third, the achievement of the labor productivity based on the objective output pattern of the economic plan for a forecast year.
- ✓ Fourth, adjusting the educational plan to fill up the gap between the anticipated qualified manpower supply and the estimates of the educational plan.

6.1 Descriptions and Notations:

The SGP approach was used at the beginning to allocate the human resources to 4 categories of manpower through fitting a MLR model to 13 indicators of human resources. Then the optimal solution might have given 5 types of estimates for:

- The slope parameters vector $\hat{\beta}' = \left\{\hat{\beta}_j \ , j = 1,2,3 \right\}$, where at,

$j = 1 : \hat{\beta}'_1 = [\hat{\beta}_{01}\ , \hat{\beta}_{11}\ , \hat{\beta}_{21}\ , \hat{\beta}_{31}\ , \hat{\beta}_{41}]$ for the independent variables $X_1 = x_1, x_2, x_3, x_4$

$j = 2 : \hat{\beta}'_2 = [\hat{\beta}_{02}\ , \hat{\beta}_{82}\ , \hat{\beta}_{92}\ , \hat{\beta}_{10,2}\ , \hat{\beta}_{11,2}]$ for the independent variables $X_2 = x_8, x_9, x_{10}, x_{11}$.

$j = 3 : \hat{\beta}'_3 = [\hat{\beta}_{03}\ , \hat{\beta}_{12,3}\ , \hat{\beta}_{13,3}]$ for the independent variables $X_3 = x_{12}, x_{13}$.

And $\hat{C}$ *as* a constant estimate for the vector X_0 of the independent variables x_5, x_6, x_7, as obtained from the logistic probability of the category y_0 , $p(y_j = 0)$,where y_o was chosen as the reference category for the other decision variables y_1, y_2, y_3.

- The probabilities of occurrence of the case status for the 4 categories:

$\hat{y}_0 = p(y = 0), \hat{y}_1 = p(y = 1), \hat{y}_2 = p(y = 2), \hat{y}_3 = p(y = 3),$

- Best evaluation of the logit functions $\hat{g}_j(x_j)$,j=1,2,3 as:

$$\hat{g}_j(x_j) = \ln\left(\frac{\hat{p}(y=j)}{\hat{p}(y=0)}\right), \qquad j=1,2,3 \qquad (6.4)$$

- The exponential function $e^{\hat{\beta}'_j}$ which describe the rate of the change in occurrence to non-occurrence ratio for each case status of the dependent variables y_j , j=1,2,3 where y_0 ,is used as a reference group,

$$e^{\hat{\beta}`_j} = \frac{p(y_j=1)/[1-p(y_j=1)]}{p(y_j=0)/[1-p(y_j=0)]} \quad , \quad j=1,2,3 \qquad (6.5)$$

Indeed this ratio is known as *odds ratio* where it is determined from the two odds ratios of y_j and y_0 occurrence as:

$$e^{\hat{\beta}`_j} = \frac{\text{odds ratio of occurrence of } y_j=1}{\text{odds ratio of occurrence of } y_0=1} \quad , \quad j=1,2,3 \qquad (6.6)$$

However the ln of $e^{\hat{\beta}`_j}$ could gives a correct definition of the slope parameters βj where it interprets the change in the logit function for a unit change in the covariate x_j [9] ,i.e.

$$\ln e^{\hat{\beta}`_j} = \hat{g}\,(x_j+I) - \hat{g}(x_j) \quad , \quad j=1,2,3 \qquad (6.7)$$

Where I is a vector of ones.

This parameter estimate in eq.(6.7) is of most interest that inferences in the MLR model are based on its sampling distribution ,where it is possible to get goodness of fit and significance tests for the assessment of the MLR model using one of the following tests:

- ✓ Likelihood ratio test
- ✓ Univariate Wald statistic
- ✓ Leverage statistic

Using any logistic program can provide the results of these tests.

Regarding the goal of the paper is to develop the human resources categories with educated personnel as a necessary condition for achieving all of the other political, cultural and socio economic goals of the progress. We should stress on some incentive factors of anticipating the high-level human resources based on the objectives of the growth plan of economy.

Assuming the development plan of manpower requirements to educational planning of [10] ,is adopted. The projected pattern of outputs for various sectors, say Q ,is predicted for a forecast year. Accordingly the total employment for the economy, say L, and for each sector X_m may be estimated on the basis of some productivity assumptions. Then the requirements of each occupation may also be evaluated by allocating the total employment for each sector among the various occupations according to the chosen occupational classification system. However a labor input matrix ,say $[X]_{N.M}$, may be available as a part of the primary inputs of the "Input-Output" Table, that relating the economic sectors with the occupational categories. Hence estimates for the coefficients matrix of labor productivity , say ,$[b]_{N.M}$ would be available as illustrated in, table(2).

Table 1: Employment Distribution among 7 Occupational Groups According to the Egyptian Classification System in Various Sectors of Economy in Recent Year:

Occupational Groups	Economic sectors					Total Employment of Occupation i
	Q_1	Q_2 ……..	Q_m	…….	Q_M	
1.Teachers	X_{11}	……			X_{1M}	$X_{1.}$
2.mangers and administration	X_{21}	……			X_{2M}	$X_{2.}$
3.professionals						.
4.technicians` assistants clerks			X_{im}			$X_{i.}$
5.services,crafts&plants						.
6.skilled agricultures						.
7.elementary jobs	X_{71}	……			X_{7M}	$X_{M.}$
Total Employment of sector j	$X_{.1}$	……	$X_{.j}$	……	$X_{.M}$	X

Table 2: Labor Productivity Matrix [b_{im}]:

Occupations code (i)	Economic sectors					Occupation Productivity
	Q_1	Q_2 ….	Q_m	….	Q_M	
1	b_{11}	b_{12}	……..		b_{1M}	$b_{1.}$
2	b_{21}	b_{22}	……..		b_{2M}	$b_{2.}$
3						.
4						.
5			b_{im}			$b_{i.}$
6						.
7	b_{71}	b_{72}	……..		b_{7M}	$b_{7.}$

Table 3: Education Outputs Productivity Matrix [V_{im}]:

Occupations code (i)	Economic sectors					Occupation Productivity
	Q_1	Q_2 ….	Q_m	…	Q_M	
8. primary level	V_{81}	V_{82}	…..		V_{8M}	$V_{8.}$
9. secondary level	V_{91}	V_{92}	…..		V_{9M}	$V_{9.}$
10. 1st&2nd technical level						.
11.higher level			V_{im}			.
12.graguates(theoretical)						.
13.graguates(scientific)	$V_{13,1}$	$V_{13,2}$	…..		$V_{13,M}$	$V_{13,.}$

Where the symbols of the previous tables can be defined as follows:

X_{im} :denotes the labor requirements from occupation i for sector m, i=1,2,…,N , m=1,2,…,M , N is the number of occupations, M is the number of sectors.

Q_m : the anticipated output of sector m for the forecast year,, m=1,2,…,M, M is the number of economic sectors according to the national accounts divisions of the economy.

b_{im} : labor input from occupation i per one unit production of sector m. It is known as the productivity coefficients matrix, say $[b]_{N.M}$, where:

$b_{im} = \frac{X_{im}}{Q_m}$ i=1,2,...,7, m=1,2,...,M.

$b_{i.} = \sum_{m=1}^{M} b_{im}$ be the labor requirements of occupation i per one unit of each sector aggregated over M sectors.

$X_{i.} = \sum_{m=1}^{M} b_{im} Q_m$, i=1,2,...,7 ,gives the requirements for each occupational category as aggregated from the various sectors to represent the total stocks required in the forecast year

$X_{.m} = \sum_{i=1}^{7} b_{im} Q_m$, m=1,2,...,M ,gives the total employments for the forecast year in sector m as allocated among the various occupations.

However given the productivity matrix $[b]_{7.M}$ and the predicted vector of production Q for a present or near future period, it is possible to estimate the projected labor requirements for each occupation for a forecast year according to the I-O analysis system of prediction ,[6],[8].

Moreover assuming the productivity coefficient matrix ,say v_{im}, i=8,...,13 of the educational outputs of the first, second , third level and higher level graduates are available from the education system as shown in Table (3).

Consider the matrix $[\Omega]_{N,M}=[b]_{7.M} + [V]_{6.M}$,

Then the predicted labor resources are obtained from the following equation:

$$[X]_{N.1} = [\Omega]_{N.M} [Q]_{M.1} \quad ,N=13 \qquad (6.8)$$

Let

$\lambda_{im} = \frac{X_{im}}{X_{i.}}$ be the labor proportion of occupation i required by sector m, then

$$b_{im} = \frac{\lambda_{im} X_{i.}}{Q_m} \quad i=1,2,...,7\ ,\ m=1,2,...,M$$

$$v_{im} = \frac{\lambda_{im} X_{i.}}{Q_m} \quad i=8,2,...,13\ ,\ m=1,2,...,M$$

As shown in table(4).

Table 4: Labor Proportional Share Matrix [λ_{im}]:

Occupations code	Productivity economic sectors Q_1 Q_2 .... Q_m ..... Q_M	$\sum_{m=1}^{M} \frac{\lambda\ im}{Qm}$	Occupation sum	$b_{i.}$
1	λ_{11} λ_{12} ... λ_{1M}	$\sum_{m=1}^{M} \frac{\lambda_{1m}}{Q_m}$	$x_{1.}$	$b_{1.}$
2	λ_{21} λ_{22} ... λ_{2M}		$x_{2.}$	$b_{2.}$
3	. .		.	.
4	. .		.	.
5	. λ_{im} .	$\sum_{m=1}^{M} \frac{\lambda_{im}}{Q_m}$	$x_{i.}$	$b_{i.}$
6	. .		.	.
7		$\sum_{m=1}^{M} \frac{\lambda_{7m}}{Q_m}$	$x_{7.}$	$b_{7.}$
8			$X_{8.}$	$V_{8.}$
9			.	$V_{9.}$
10			.	.
11			.	.
12				.
13	$\lambda_{13,1}$ ... ... $\lambda_{13,M}$	$\sum_{m=1}^{M} \frac{\lambda_{13,m}}{Q_m}$	$X_{13,.}$	$V_{13,.}$

Then assuming the following estimates are given as follows:

L_1 : be the anticipated manpower vector as divided into high and low level of educated qualification , L_1 , L_0 ,where $L_1 = x_{1,1}, x_{2,1}, x_{3,1}, x_{4,1}$, $L_0 = x_{5,0}, x_{6,0}, x_{7,0}$

L_2 : be the anticipated outflows from the existing educational system(primary, secondary & high level) ,where $L_2 = x_{82}, x_{92}, x_{10,2}, x_{11,2}$,as presently planned for the forecast year.

L_3 : be the anticipated graduated personnel from the theoretical and scientific colleges for the forecast year where $L_3 = x_{12,3}, x_{13,3}$.

The labor personnel categories as anticipated by L_0 , L_1 , L_2 , L_3 through the economic and educational outflows can be considered as the present labor force supply for the forecast year. Hence the governmental education system must adjust the education plan to fill in the gab between its anticipated requirements and the presently expected supply of the manpower needs.

6.2 Construction of the SGP model of Predicting the human resources:

Now we are applying a SGP model once more to introduce optimal estimates for the anticipated requirements of the human resources X_{im} ,for the governmental development policy as detailed before ,under the following goals, where the first two goals are to validate and achieve the MLR optimal solution ,while the other two goals are to satisfy the economic and educational development plans.

Let:

$F_j(X)$,$F_j(\beta)$ are the cumulative functions of X, β respectively.

$F_j^{-1}(x), F_j^{-1}(\beta)$ are the inverse of the cumulative distribution function of X, β,

α_j ,□j are tolerance measures , j=0,1,2,3 ,

0< α_j , □j < 1

τ_j is the number of independent variables included in category j.

First set of goals: achieving optimal estimates of the human resources with the highest possible probabilities:

We want to obtain estimates for the labor resources groups x_j ,j=0,1,2,3 using the inverted solution of the MLR to the fullest possible extent with probabilities greater than or equal α_j .Consider the random variables X_j have MLR distribution with parameters' vector ß=[$ß_0$ $ß_1$ $ß_2$ $ß_3$] of the logistic density function $f_j(x_j)$,

$$f_j(x_j)=\frac{e^{\beta'_j x_j}}{1+\sum_{j=1}^{3} e^{\beta'_j x_j}} \quad ,j=0,1,2,3 \ , \qquad (6.9)$$

x_j is a vector $[x_{ij}]$,i=1,...,τ_j ,j=0,1,2,3 , β_0 =0

where the parameters are stochastically estimated *by* $\widehat{\beta_j}$,j=1,2,3, $ß_0$=0.Then the cumulative functions of x_j ,j=0,1,2,3 ,[4] at a reliability measure α_j are:

$$F(x_0)=\frac{X_0}{1+\sum_{j=1}^{3} e^{\widehat{\beta}'_j x_j}} = \alpha_0 \qquad (6.10)$$

$$F(x_j)=\frac{1}{\sum_{i=0}^{\tau j} \hat{\beta}_{ij}} \sum_{i=0}^{\tau j} \hat{\beta}_{ij} x_{ij} = \alpha_j \ , j = 1,2,3 \ , x_{0j} = 1 \qquad (6.11)$$

$$X_0 - \alpha_0 \sum_{j=1}^{3} e^{\widehat{\beta}'_j x_j} = \alpha_0 \qquad (6.12)$$

$$\sum_{i=0}^{\tau j} \hat{\beta}_{ij} x_{ij} = \alpha_j \sum_{i=0}^{\tau j} \hat{\beta}_{ij} \qquad (6.13)$$

Then using the chance constrained method [5],[18] to obtain the transformed equivalent deterministic goal program of the SGP model and choosing the tolerance measure α_j =0.95 we can determine the human resources x_{ij} which satisfy the following set of goals:

$$x_0 - \alpha_0 \sum_{j=1}^{3} e^{\widehat{\beta}'_j x_j} + d_{01}^{-} - d_{01}^{+} = \alpha_0$$

$$\sum_{i=1}^{4} \hat{\beta}_{i1} x_{i1} + d_{11}^{-} - d_{11}^{+} = \alpha_1 \sum_{i=0}^{4} \hat{\beta}_{i1} = u_1$$

$$\sum_{i=8}^{11} \hat{\beta}_{i2} x_{i2} + d_{12}^{-} - d_{12}^{+} = \alpha_2 \sum_{i=8}^{11} \hat{\beta}_{i2} = u_2$$

$$\sum_{i=12}^{13} \hat{\beta}_{i3} x_{i3} + d_{13}^{-} - d_{13}^{+} = \alpha_3 \sum_{i=12}^{13} \hat{\beta}_{i3} = u_3$$

Where:

d_{1j}^{-} : represents the negative deviation variable of labor personnel not utilized in the labor category j ,i.e. pr[u_j-$\sum_{i=1}^{\tau j} \hat{\beta}_{ij} x_{ij}$ $\square$ d_{1j}^{-}]=α_j ,j=1,2,3.

d_{1j}^{+} : represents the positive deviation variable of labor personnel over utilized in the labor category j ,j=1,2,3 ,i.e., pr[$\sum_{i=1}^{\tau j} \hat{\beta}_{ij} x_{ij} - u_j$ $\square$ d_{1j}^{+}] =$1 - \alpha_j$,j=1,2,3.

Second set of goals: Best allocation of human resources:

As in the MLR distribution the functional relationship between the dependent and independent variables is the logit transformation measure $g_j(x_j)$ = $\sum_{i=0}^{\tau j} \hat{\beta}'_j x_j$ [12] ,where the slope coefficients estimates $\hat{\beta}'_j$ represents the change rate of the logit function per unit change in the independent variable x_j .And we have 3 logit functions for the three outcome dependent variables y_j ,j=1,2,3 ,using y_0 as reference group. The optimal evaluation of the logit function could be given by:

$$\hat{g}_j(x_j) = \ln\left(\frac{\hat{P}((y=j|x))}{\hat{P}(y=0|x)}\right) \qquad ,j=1,2,3 \qquad (6.14)$$

Where $g_0(x_0)=0$ as $\beta_0=0$

The second set of goals is hence to determine the variables x_{ij} so as the optimal allocation of the human resources x_j are correctly specified to their outcome categories with probability more than or equal α_j ,considering the following notes:

Since X_0 =(x_{50} ,x_{60}, x_{70}) has MLR distribution with density $f(x_0)$ and cumulative function at the tolerance measure α_0 , $F(x_0)$,then $F^{-1}(\alpha_0)$= X_0.Also having in theory the distribution of $e^{\widehat{\beta}_j}$ is normal and hence $\ln e^{\widehat{\beta}_j}$ tends to follow normal distribution[12] ,then the estimates vector $\hat{\beta}$ =$\hat{\beta}_1$,$\hat{\beta}_2$, $\hat{\beta}_3$ are random variables with normally distributed pdf and distribution function at the tolerance measure γ_j ,$F_j(\beta_j)$ = γ_j ,the stochastic goal set is:

$\Pr[g_j(x_j)$ □ $\ln\left(\frac{\hat{P}(y=j)}{\hat{P}(y=0)}\right)] = 1 - \gamma_j$,j=1,2,3 (6.15)

Then , deterministically, the second set of goals is:

$$x_{50} + x_{60} + x_{70} + d_{20}^{-} - d_{20}^{+} = \mathrm{F}^{-1}(\alpha_0)$$

$$\mathrm{F}^{-1}(\gamma_1)\sum_{i=1}^{4} x_{i1} + +d_{21}^{-} - d_{21}^{+} = \ln\left(\frac{\hat{P}(y=1)}{\hat{P}(y=0)}\right)$$

$$\mathrm{F}^{-1}(\gamma_2)\sum_{i=8}^{11} x_{i2} + +d_{22}^{-} - d_{22}^{+} = \ln\left(\frac{\hat{P}(y=2)}{\hat{P}(y=0)}\right)$$

$$\mathrm{F}^{-1}(\gamma_3)\sum_{i=12}^{13} x_{i3} + +d_{23}^{-} - d_{23}^{+} = \ln\left(\frac{\hat{P}(y=2)}{\hat{P}(y=0)}\right)$$

Where:

d_{2j}^{-} : represents the lower level of negative deviation of random allocation from the expected allocation of human resources x_{ij} to the human category j i.e.,
pr[$\ln\left(\frac{P(y=j)}{P(y=0)}\right) - \hat{g}_j(x_j)$ □ d_{2j}^{-}]= γ_j ,j=1,2,3

d_{2j}^{+} : represents the lower level of positive deviation of random allocation from the expected allocation of human resources x_{ij} to the human category j , i.e.,

pr[$\hat{g}_j(x_j) - \ln\left(\frac{P(y=j)}{P(y=0)}\right)$ □ d_{2j}^{+}]=1-γ_j ,j=1,2,3

Third set of goals: Achieving of prospective productivity policy:

Consider the matrix of labor productivity could be calculated for M sectors of production and N occupations as coded by [b_{im}] i=1,2,...7 ,m=1,2,...,M as shown in table(2). Assuming the productivity contribution of the three levels of education and of the recent graduates are available in abbreviated matrix [v_{im}],i=8...,13 as shown in table (3).Then the 13 human resources as described before by x_{ij} ,j=1,2,3 aimed to be determined such that the projected outputs vector Q of the national economy`s sectors are satisfied according to the I-O forecasting system. However given the productivity matrices b, v and the proportional occupation shares matrix λ ,the joint matrix $\frac{\lambda_{im} x_{i.}}{Q_m}$ of occupations shares and productivity coefficients ,as illustrated in table(4) would be used to achieve the linear goals:

$$\sum_{i=1}^{\tau j}\left(\sum_{m=1}^{M}\frac{\lambda_{im}}{Q_m}\right)x_i = \sum_{i=1}^{\tau j} b_{i.} \quad ,j=0,1,2,3$$

The third set of goals is to find x_{ij} i=1,...7,j=0,1,2,3 which satisfy the following for each category j as:

$\sum_{m=1}^{M}\left(\frac{\lambda_{5m}}{Q_m}\right)x_{50}+\sum_{m=1}^{M}\left(\frac{\lambda_{6m}}{Q_m}\right)x_{60}+\sum_{m=1}^{M}\left(\frac{\lambda_{7m}}{Q_m}\right)x_{70}+d_{30}^{-}-d_{30}^{+}=\sum_{i=5}^{7}\text{b}_{\text{i.}}$

$\sum_{m=1}^{M}\left(\frac{\lambda_{1m}}{Q_m}\right)x_{11}+\sum_{m=1}^{M}\left(\frac{\lambda_{2m}}{Q_m}\right)x_{21}+\sum_{m=1}^{M}\left(\frac{\lambda_{3m}}{Q_m}\right)x_{31}+\sum_{m=1}^{M}\left(\frac{\lambda_{4m}}{Q_m}\right)x_{41}+d_{31}^{-}-d_{31}^{+}=\sum_{i=1}^{4}\text{b}_{\text{i.}}$

$\sum_{m=1}^{M}\left(\frac{\lambda_{8m}}{Q_m}\right)x_{81}+\sum_{m=1}^{M}\left(\frac{\lambda_{9m}}{Q_m}\right)x_{91}+\sum_{m=1}^{M}\left(\frac{\lambda_{10,m}}{Q_m}\right)x_{10,1}+\sum_{m=1}^{M}\left(\frac{\lambda_{11,m}}{Q_m}\right)x_{11,1}+d_{32}^{-}-d_{32}^{+}=\sum_{8=1}^{11}\text{V}_{\text{i.}}$

$\sum_{m=1}^{M}\left(\frac{\lambda_{12,m}}{Q_m}\right)x_{12,1}+\sum_{m=1}^{M}\left(\frac{\lambda_{13,m}}{Q_m}\right)x_{13,1}+d_{33}^{-}-d_{33}^{+}=\sum_{i=12}^{13}\text{V}_{\text{i.}}$

Fourth set of goals: filling the gab between the required labor supply and the anticipated outputs of educational plan:

Assuming the labor supply projection of the development plan provided the anticipated labor stock L_0,L_1 as identified with their educational qualification and the presently anticipated educational outflows L_2, L3.From the existing educational system ,the following set of goals aim at determining the human resources X_{ij} ,i=1,...,13 which satisfy the planned supply so that $\sum_{i=1}^{\tau j}x_{ij}\geq L_j$,j=0,1,2,3 .It must take into account the rate of economic production growth r_g which is resulting in increasing high level labor due to the increased productivity. Also the rates of losses in educational outflows due to the penetration r_e and death r_a ratios must be considered. Then the fourth set of goals is:

$\sum_{i=5}^{7}x_{i0}\ +d_{40}^{-}-d_{40}^{+}=L_0$

$\sum_{i=1}^{4}x_{i1}\ (1+r_g)\ +d_{41}^{-}-d_{41}^{+}=L_1$

$\sum_{i=8}^{11}x_{i2}\ (1-r_e)\ +d_{42}^{-}-d_{42}^{+}=L_2$

$\sum_{i=12}^{13}x_{i3}\ (1-r_a)\ +d_{43}^{-}-d_{43}^{+}=L_3$

Where

d_{4j}^{-} :are the shortage of labor requirements to satisfy labor supply plan.

d_{4j}^{+} :are the surplus of labor requirements over the predicted labor supply plan.

From the previous descriptions the SGP can be formulated deterministically as follows:

Min. a $=\sum_{j=0}^{4}\left(d_{1j}^{-}+d_{1j}^{+}\right)+\sum_{j=0}^{4}\left(d_{2j}^{-}+d_{2j}^{+}\right)+\sum_{j=1}^{4}\left(d_{3j}^{-}\right)+\sum_{j=1}^{4}\left(d_{4j}^{-}\right)$

s.t.

$$\text{x}_0-\alpha_0\sum_{j=1}^{3}e^{\overline{\beta}_j x_j}+d_{01}^{-}-d_{01}^{+}=\alpha_0$$

$\sum_{i=1}^{4}\hat{\beta}_{i1}x_{i1}++d_{11}^{-}-d_{11}^{+}=\alpha_1\sum_{i=0}^{4}\hat{\beta}_{i1}=u_1$

$\sum_{i=8}^{11} \hat{\beta}_{i2}x_{i2}++d_{12}^{-} - d_{12}^{+} = \alpha_2 \sum_{i=8}^{11} \hat{\beta}_{i2}^{`} = u_2$

$\sum_{i=12}^{13} \hat{\beta}_{i3}x_{i3}++d_{13}^{-} - d_{13}^{+} = \alpha_3 \sum_{i=12}^{13} \hat{\beta}_{i3}^{`} = u_3$

$x_{50} + x_{60} + x_{70} + d_{20}^{-} - d_{20}^{+} = F^{-1}(\alpha_0)$

$F^{-1}(\gamma_1) \sum_{i=1}^{4} \hat{\beta}_{i1}x_{i1}++d_{21}^{-} - d_{21}^{+} = \ln\left(\frac{\hat{P}(y=1)}{\hat{P}(y=0)}\right)$

$F^{-1}(\gamma_2) \sum_{i=8}^{11} \hat{\beta}_{i2}x_{i2}++d_{22}^{-} - d_{22}^{+} = \ln\left(\frac{\hat{P}(y=2)}{\hat{P}(y=0)}\right)$

$F^{-1}(\gamma_3) \sum_{i=12}^{13} \hat{\beta}_{i3}x_{i3}++d_{23}^{-} - d_{23}^{+} = \ln\left(\frac{\hat{P}(y=2)}{\hat{P}(y=0)}\right)$

$\sum_{m=1}^{M}\left(\frac{\lambda_{5m}}{Q_m}\right)x_{50}+\sum_{m=1}^{M}\left(\frac{\lambda_{6m}}{Q_m}\right)x_{60}+\sum_{m=1}^{M}\left(\frac{\lambda_{7m}}{Q_m}\right)x_{70}+d_{30}^{-}-d_{30}^{+}=\sum_{i=5}^{7} b_{i.}$

$\sum_{m=1}^{M}\left(\frac{\lambda_{1m}}{Q_m}\right)x_{11}+\sum_{m=1}^{M}\left(\frac{\lambda_{2m}}{Q_m}\right)x_{21}+\sum_{m=1}^{M}\left(\frac{\lambda_{3m}}{Q_m}\right)x_{31}+\sum_{m=1}^{M}\left(\frac{\lambda_{4m}}{Q_m}\right)x_{41}+d_{31}^{-}-d_{31}^{+}=\sum_{i=1}^{4} b_{i.}$

$\sum_{m=1}^{M}\left(\frac{\lambda_{8m}}{Q_m}\right)x_{81}+\sum_{m=1}^{M}\left(\frac{\lambda_{9m}}{Q_m}\right)x_{91}+\sum_{m=1}^{M}\left(\frac{\lambda_{10,m}}{Q_m}\right)x_{10,1}+\sum_{m=1}^{M}\left(\frac{\lambda_{11,m}}{Q_m}\right)x_{11,1}+d_{32}^{-}-d_{32}^{+}=\sum_{8=1}^{11} V_{i.}$

$\sum_{m=1}^{M}\left(\frac{\lambda_{12,m}}{Q_m}\right)x_{12,1}+\sum_{m=1}^{M}\left(\frac{\lambda_{13,m}}{Q_m}\right)x_{13,1}+d_{33}^{-}-d_{33}^{+}=\sum_{i=12}^{13} V_{i.}$

$\sum_{i=5}^{7} x_{i0} + d_{40}^{-} - d_{40}^{+} = L_0$

$\sum_{i=1}^{4} x_{i1}\ (1+r_g) + d_{41}^{-} - d_{41}^{+} = L_1$

$\sum_{i=8}^{11} x_{i2}\ (1-r_e) + d_{42}^{-} - d_{42}^{+} = L_2$

$\sum_{i=12}^{13} x_{i3}\ (1-r_a) + d_{43}^{-} - d_{43}^{+} = L_3$

$d_{kj}^{-}, d_{kj}^{+}, x_{ij} \geq 0 \quad d_{kj}^{-} * d_{kj}^{+} = 0$, j=1,2,3 ,i=1,...,τ_j, k is the number of sets of goals.

Conclusion:

In the paper a method of estimating the future manpower requirements for the educational planning is introduced to meet the anticipated labor supply of the development policy. It links manpower needs to productivity and is designed to identify the high level manpower into two main categories, human capital stock and additions to this stock from the educational outputs who have at least 12 years of education .The contributed labor resources are first correctly allocated to their human categories using MLR and then optimally estimated using the inverted MLR parameters` estimates. In the two stages the SGP technique is applied with 4 groups of objectives relies on validating the optimality of the MLR results using the variables of significance and goodness of fit tests as goals in the first 2 groups and the other 2 groups of objectives are based on the anticipated productivity plan of the educational professional and qualified labor. Though in some sectors the productivity criteria may be of shortage indicator but the availability of statistical information system would save adequate treatment. The efficiency of the applicable ability of this method to be perfórmed empirically, specially to the Egyptian data is basically assessed by choosing the MLR model to represent the multiple outputs of employment categories .Moreover the causes and rational using of SGP model solution is the need to obtain the best estimates for the human strategic labor resources which is usually available in the SGP technique. However we fitted the MLR distribution and preferably used the SGP than the maximum likelihood method in solving the twofold model.These two techniques are extremely appropriate to represent and estimate the two flow of manpower since they are more efficient and accurate in empirical applications[1]. Also the paper provided a matched of 1-3 case control probabilities of the 4 outcomes of the model. In the nearest subsequent period this work will be extended to introduce an application of the suggested models to the case of Egyptian economy with the same classification of occupations as distributed among a number of 8 economic sectors.

Acknowledgment

I m deeply appreciate the great offer and the kind help of D .Rokia Soliman in each part of the paper.

References:

1- Anas,A,2009,Mathematical Programming Approach to Multinomial logistic Regression, M.SC Thesis, Faculty of Economic & Political Science , Statistical Department, Cairo University, Egypt.
2- Bachrach,M ,Melnces,B, Input-Output Changes,1970, Cambridge University Press, USA.
3- Balakrishnan,N, 1992, Hand Book of Logistic Distribution, Marcel Dever, Inc, New York.
4- Capmas Publishing,2013, Statistical Year Book, Employment Sector, Cairo, Egypt.
5- Charnes ,A. and Cooper, W.W, 1977, Goal Programming and Multiple Objectives Optimizations. European Journal of Operational Research,1, 39- 54.
6- Economic Papers,1978, Polish Egyptian Seminar held in Warsaw on CSPS Research Institute for Developing Countries.
7- Glynm,J.G, 2012, A Goal Programming Approach to Human Resource Planning with a Concentration on Promotion Policy, Journal of Business & Economic Research , 3(3), p 71-80
8- Glass.C,J,1980,An Introduction to mathematical methods in economics, MC Graw Hill book Company U.K.

9- Hosmer,D.W & Lemshow,s,2013,Applied Logistic Regression, Willey series in Probability & Mathematical Statistics ,John Wiley & Sons ,New York.

10- Horbison,F.E,& Myers,C.A, 1974, Education, Manpower and Economic Growth: Strategies of Human Resources Developments, Oxford & IBH Publishing Co.

11- Ignizio.J ,1976, Goal Programming and Extensions, Lexington, MA Lexington Books.

12- Kotz,S ,Johenson,N.L, 1995,Continuous univariate distributions, John Wiley &Sons, New York.

13- Pindyck,R.S & Rubinfeld,D.L, 1998, Econometric Models and Economic Forcasts, Graw Hill book Company U.K, Economic series.

14- Stone,R ,1961,Input-Output and National Account, Organization for Economic Cooperation and Development, Paris.

15- Tintiner,G & Sengupta, J.K,1972 ,Stochastic economic, Stochastic processes, control and programming, Academic Press, New York.

16- Yang,K & Ming,W,2007,Using ANP priorities with goal programming in resource allocation ,Mathematical &Computer Modeling,46,885-1000.