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A SIMULATION MODEL FOR AGED AND DISABLED SERVICES

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ABSTRACT

A new approach to large-scale simulation modeling for policy analysis in the public sector is described in this paper. The model differs from conventional microanalytic models that have previously been used. Whereas conventional microanalytic models extrapolate the detailed behavior of a representative sample of individuals to the corresponding target population, the new technique disaggregates an exogenous demographic forecast into enough detail to evaluate the impact of proposed social programs. The methodology is demonstrated in a prototype decision support system for analysis of the Institutional Care and Community Care programs of the Texas Department of Human Resources. This approach uses a multivariate extension of Johnson's univariate translation systems in order to estimate the percentage of a target population who satisfy alternate program eligibility criteria. The new approach appears to be more acceptable than conventional microanalytical simulation for the analysis of public policy decisions.

INTRODUCTION

This paper reports the results of an effort to develop a large-scale computer simulation for public policy analysis [1,2]. The study was a component of a major research effort that was concerned with the enhancement of policy development and analysis for the Texas Department of Human Resources (TDHR) [3]. The reduction, at least in terms of constant dollars, in resources that are available to public welfare organizations coupled with the changes in their roles and responsibilities has led to a need for more rigorous policy analysis. In developing and analyzing policy options, decision makers are forced to match resources with objectives, and to identify those actions which most effectively contribute to the solving of a set of problems. This research effort was carried out in conjunction with the staff of the TDHR. It seemed logical, given some of the work that had already been done in the use of computer simulations in the development of public policy [4], for us to attempt to use simulation modeling in our efforts. We worked closely with agency staff to identify managerial, technical and political problems associated with the design and implementation of computer simulation techniques for public policy analysis.

One of the initial findings of our investigation was that there were serious problems facing the agency if they attempted to use traditional microanalytical simulation modeling techniques that had been previously used for public policy analysis [4,5,6,7]. Some of these were technical problems primarily revolving around the availability of the data required to drive these models, and some were political, primarily revolving around the difficulty decision makers often have in understanding these models.

As an alternative to the traditional models a new top down perspective is suggested. A simulation model is proposed that relies upon disaggregating given demographic forecasts into enough detail so as to evaluate the impact and cost of proposed social programs. The analysis required techniques for estimating the percentage of individuals in a target population that is defined by ten service regions and eight age cohorts and who satisfy alternative program eligibility criteria. A multivariate extension of Johnson's univariate translation systems [8,9] is developed for this purpose. The model is demonstrated by way of a prototype decision support system for analyzing welfare services provided to the aged and disabled population of Texas. The resulting simulation model is more technically and politically acceptable than traditional microanalytical models. Consequently, this new modeling approach may have broad applications for enhancing public policy decisions.

A FRAMEWORK FOR PUBLIC POLICY ANALYSIS

One of the most critical tasks in the analysis of welfare programs is the estimation of the social impacts and costs of alternative means of service delivery. As the use and distribution of public resources is scrutinized more closely the task of improving these forecasts is particularly important. These forecasts are used in the political processes that determine which social programs merit public funding and to the extent that these forecasts are accurate and believable, then public decision makers are able to make informed decisions about the allocation of resources. The credibility of an agency and the relative influence that the agency will have in decision making is directly related to accuracy and believability of forecasts made by the agency. A number of groups, both inside and outside of TDHR participate in setting policy. Therefore, projections of cost and impact must be developed that can withstand the scrutiny of a wide variety of audiences. For example, if an analysis concerns decisions affecting the appropriations process, then those responsible for that process will want to review not only the outcomes of the analysis but also the methodology used to arrive at those outcomes.

Historically, government agencies have not been as successful as they would like in estimating the need for and the utilization of public services [4,10,11]. A number of explanations for this have been suggested [11,12]. It has been suggested, for example, that agencies deliberately overestimate the need for public services in order to increase the chances of favorable political action. Other explanations focus on a lack of managerial competence and/or the unavailability of adequate estimation techniques. While recognizing the plausibility of these kinds of explanations, we saw the decision maker as faced with a formidable analytical problem; how to best evaluate the policy options available for addressing a particular policy problem [10,11,13].

Two major sets of policy variables must be considered by the decision maker faced with the task of policy analysis in a welfare setting. The first set of variables to be considered are the combination of program options available for a given problem. Each option has variable participation rates and variable costs per unit of service. While each program option will serve some identifiable subset of the eligible population, the agency has some choice in determining how it will organize and deliver a given program of service. Policy choices must, therefore, be made that affect both the participation rate and the cost per unit of service.

The second set of variables relate to client eligibility. This is usually determined, in welfare situations, by an income needs test and a functional needs test. In order to be eligible for welfare assistance, a person must be poor and sick, or poor and a single parent, or poor and out of work. The common denominator of poverty is measured by income and resources. It should be noted that the three variables of income, resources, and functional need may not be independent of each other. The problem of forecasting the impact of a given policy decision includes estimating the size of the client pool under a variety of policy options.

In addition to these policy variables, there are two sets of environmental variables that must be considered in attempting to determine the potential impact of policy decisions. The environmental variables in the first set describe the change in the inflation rates for the cost of service and the second set describes the change in size and composition of the target population over time. Such exogenous variables cannot be controlled by the policy maker, and in fact, they may be constrained by law (women and men must be treated the same for retirement programs although they have different actuarial histories), by technology (psychiatric intervention procedures are often very unpredictable), or by public opinion (the aged should be given options as to their life styles). Policy analysis involves estimating the impact of a variety of policy variables under a wide range of conditions and assumptions.

This research focused on developing a simulation model that would be transparent and acceptable to the political actors ultimately responsible for the policy decisions. The model also had to be analytically sound and practicable. Figure 1 shows the complex interaction of policy and environmental variables that needed to be considered. In order to achieve these goals a new perspective on public policy simulation was developed and implemented by way of a prototype decision support system.

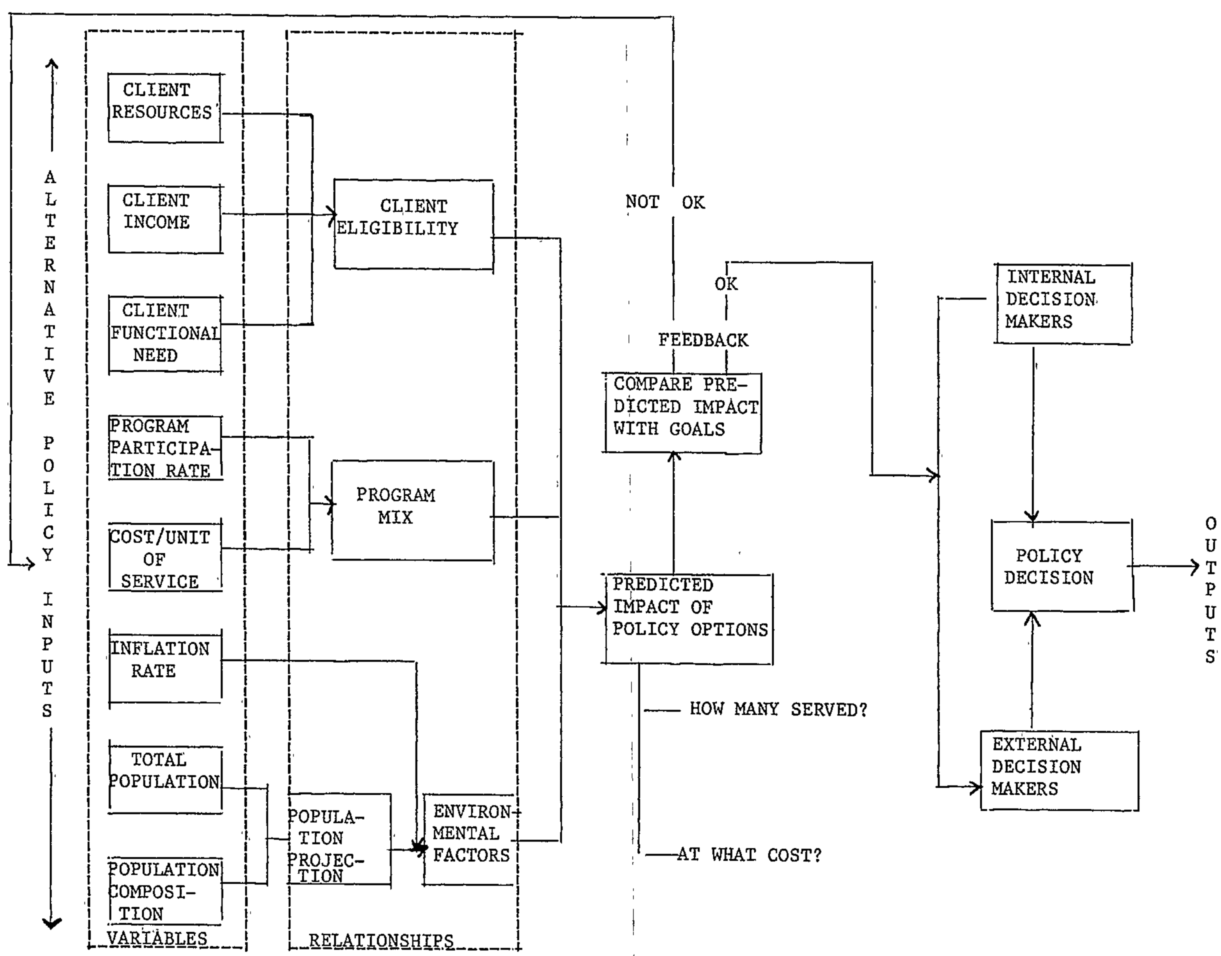

FIGURE 1. Policy analysis process.

SIMULATION MODELS PREVIOUSLY USED FOR POLICY ANALYSIS

Computer simulation models for public policy analysis have been available for nearly two decades [5]. A catalyst for the development of these models was the surge in federal spending for welfare programs accompanying Lyndon Johnson's "War on Poverty." In the mid-1960s, federal legislation involving billions of dollars was being introduced in Congress to address various social issues. Yet at that time, neither the analytical tools nor the data were available to government analysts for answering questions about the impact and costs of the proposed social programs. Crude estimates and sometimes distorted facts were used as the basis for making policy recommendations [4].

Weak public policy analysis was thought to be an impediment to passing federal legislation. Consequently, analysts at the Department of Health, Education, and Welfare (HEW) and the Office of Economic Opportunity (OEO) supported the development of a general purpose computer simulation model for analyzing proposed income transfer programs. In 1968, the President's Commission on Income Maintenance Programs sponsored the development of a microanalytic simulation model known as RIM (Regional Income Model) [7]. Despite simplistic relations and crude data, RIM was extensively used at HEW and OEO. Subsequent modeling efforts undertaken by the Urban Institute resulted in two more sophisticated analysis programs: TRIM (Transfer Income Model) [6], and DYNASIM (Dynamic Simulation of Income Model) [5]. TRIM in particular has been widely adopted by many federal agencies including the Department of Housing and Urban Development (HUD) and the Congressional Budget Office, as well as by many private organizations interested in demographic projections for the United States. However, there are no reports of state agency applications of TRIM.

Microanalytic simulation models could be used to analyze proposed social programs at the state level. However, the models have several characteristics that impede their adoption. The most important is the amount and quality of data needed to use the models. Such data simply are not available at the TDHR in any readily usable form. Another deterrent is the complexity of the functional relationships used in the models. These relationships are not transparent to the analysts nor to the policy decision makers. Microanalytic simulation models focus on a microcosm made up of a representative sample of individuals or households. This initial sample generally is derived from census data, and it contains sufficient detail to reflect the policy changes being investigated. These models also require estimates of the rates of change in demographic characteristics. The rates are used to "age" the sample to determine the impact and cost of proposed social programs. The impact on the sample is then extrapolated to the entire projected population. The complexity of the models and the large amounts of data required make microanalytic simulation models intimidating to use, especially if analysis is required rapidly and repetitively under different program conditions.

Despite the problems with microanalytic simulation models, high-level personnel at the TDHR believed that some type of simulation modeling in the form of a decision support system should be used for policy analysis. A computer simulation committee made up of analysts, program directors, and outside university advisors was established to detail the specifications for a decision support/simulation model. The committee decided that any such model should be easy to use and allow for rapid analysis, it should allow for systematic changes in policy variables with all assumptions being surfaced, it should be statistically valid yet require only data readily available to the TDHR, and it should use a form of analysis transparent and acceptable to decision makers.

ADSSIM: AGED AND DISABLED SERVICES SIMULATION MODEL

Modeling Objectives

ADSSIM was developed as an impact evaluation and forecasting tool for the Institutional Care and Community Care Programs of the TDHR [1,2,3]. It enables policy analysts to anticipate the effects of changes in program eligibility criteria on client loads, on costs, and on other relevant measures. It also enables decision makers to forecast these measures for new and existing services over an extended planning horizon. ADSSIM was designed to make the best use of available data, and to be as consistent as possible with accepted procedures for evaluating new and existing programs. Consequently, the model had to be structurally valid, transparent to analysts and to decision makers, and practicable for implementation. ADSSIM is a prototype model that is intended to help frame future decision support systems for the TDHR.

ADSSIM takes an entirely different tack for developing projections. Whereas microanalytic models extrapolate an "aged" sample to the entire population, ADSSIM relies upon disaggregating a given forecast into enough detail so as to evaluate the impact and cost of proposed programs. This top-down approach recognizes that many different population forecasts are available to various state agencies, and program analysis must be consistent with the forecasts adopted. For example, demographic forecasts used by the Governor's Office are likely to be different from those used by the Legislature. With ADSSIM, almost any demographic forecast can be selected to drive the model.

Model Structure

ADSSIM is interactive, user-friendly, and flexible. It leads the analyst through the structure of a particular policy option so that all policy variables and assumptions are surfaced as the analyst responds to a sequence of questions. In most cases, the analyst can choose to use default values for various inputs, or the analyst can enter new values as deemed appropriate.

The following notation shall be used to describe the functional relations employed in ADSSIM:

$P_{i\ell t}$ = forecast for year t of the target population defined by age cohort ℓ and region i.

X_1 = monthly income for a randomly chosen person in the target population.

X_2 = dollar value of countable resources for the same randomly chosen person.

X_3 = functional disability score for the same randomly chosen person.

x°_{1j} = upper limit on the person's monthly income in order to be eligible for service j.

x°_{2j} = upper limit on the person's countable resources in order to be eligible for service j.

x°_{3j} = lower limit on the person's functional disability score in order to be eligible for service j.

$G_{i\ell}(x^\circ_{1j}, x^\circ_{2j}, x^\circ_{3j}) = \Pr\{X_1 \le x^\circ_{1j}, X_2 \le x^\circ_{2j}, X_3 > x^\circ_{3j}\}$ = percentage of persons in the target population defined by cohort ℓ and region i who are eligible for service j.

$\psi_{ij\ell t}$ = participation rate for service j that is expected to occur within the target population defined by cohort ℓ and region i during year t.

N_j = average number of units of service j required annually for each participating client.

C_j = average annual cost per unit of service j in the base year of the study.

r_j = annual rate of inflation in the cost of service j.

t° = base year of the study.

The projected number of persons in region i participating in service j during year t is given by

$$Y_{ijt} = \sum_{\ell} \psi_{ij\ell t} \cdot G_{i\ell}(x^\circ_{1j}, x^\circ_{2j}, x^\circ_{3j}) \cdot P_{i\ell t} \qquad (1)$$

The projected costs of this service by region and for the entire state are

$$K_{ijt} = Y_{ijt} \cdot N_j \cdot C_j \cdot (1 + r_j)^{t-t^\circ} \qquad (2)$$

and

$$K^*_{jt} = \sum_{i=1}^{n} K_{ijt}\ , \qquad (3)$$

where n is the number of regions in the state.

ADSSIM can provide projected client loads and costs by region and by age cohort over a designated forecast horizon. These projections can be aggregated across regions and/or across age cohorts as needed. While the projections in (2) and (3) are based on the total assumption of service costs by the TDHR, copayment programs have been proposed. ADSSIM allows for the analysis of copayment programs by specifying a monthly income level above which clients will contribute to the cost of services. Copayment is factored into the total cost projections.

Equation (1) assumes that the eligibility criteria are fixed for the forecast horizon. However, ADSSIM allows for the income and resource criteria to vary; for example, they may be indexed to the cost of living.

The ADSSIM process flow closely follows agreed upon procedures for analyzing program alternatives. These procedures involve the following steps:

1. Specify the eligibility criteria for a service. These criteria are defined in terms of income levels, resources, and a measure of functional need.

2. Acquire credible demographic forecasts for the time horizon of interest. These must be given by region and age cohort.

3. Fit a trivariate distribution to sample data of income, resources, and functional need. These shall be used to disaggregate the forecasts.

4. Apply the appropriate area of the trivariate distribution to the forecasts. This gives a forecast of the number of eligible clients for each period of the forecast horizon.

5. Apply appropriate participation rates to the projected eligible population. This yields a forecast of client loads.

6. Apply costs to projected units of service (adjusting costs as deemed appropriate for inflation) to develop projections of total service costs.

7. Perform sensitivity analysis by changing criteria or data input and by repeating the analysis.

Figure 2 illustrates the steps that comprise the ADSSIM process flow. Note that the primary "driver" of the model is the demographic forecast file that is constructed outside the model. However, the available demographic forecasts for Texas are not detailed enough to be useful for policy and program analysis. In addition to age and region, these projections must be broken down by income, resources, and a measure of functional need. Eligibility criteria for services often include all of these variables. This involves estimating the trivariate distribution functions $G_{ij}(x^\circ_{1j}, x^\circ_{2j}, x^\circ_{3j})$ for all service regions and age cohorts as well as arbitrary values of the eligibility limits $x^\circ_{1j}, x^\circ_{2j}, x^\circ_{3j}$. The TDHR conducts a biennial survey that can record among other things income, resources, and functional disability scores. This sample would be the appropriate basis for estimating these distributions.

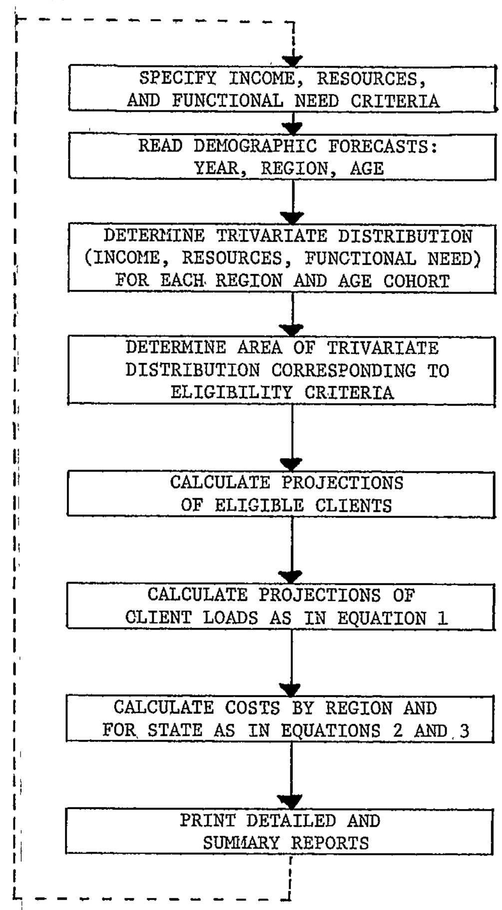

FIGURE 2. ADSSIM PROCESS FLOW

MODELING THE TRIVARIATE TARGET POPULATIONS

Johnson's Univariate Translation Systems

In this study as in many other practical applications, marked departures from normality were observed in many of the univariate data sets that were encountered. Since statistical theory for normally distributed populations is much simpler and more extensively developed than for any other underlying distribution, there is a strong motivation to seek a one-to-one transformation of the original data that will yield normally distributed observations. At least in principle, this can always be done; and then relevant percentages for each univariate target population can be obtained by computing the corresponding normal probabilities.

Suppose that the continuous random variable X has the (unknown) distribution function $F_X(x) = \{\Pr X \leq x\}$, $-\infty < x < +\infty$. To translate X into a new variate Z having the standard normal distribution $\Phi_1(z) \equiv \Pr\{Z \leq z\} = (2\pi)^{-1/2} \int_{-\infty}^{z} \exp(-1/2 t^2)\, dt$ $(-\infty < z < +\infty)$, Johnson [8] proposed several transformations having the general form

$$Z = \gamma + \delta \cdot f[(X - \xi)/\lambda] \quad (\delta > 0,\ \lambda > 0). \tag{4}$$

If on the other hand we start with a variate $Z \sim \Phi_1$, then the selection of a particular function $f(\cdot)$ implicitly defines a family (or system) of distributions for X; and we seek to approximate the target distribution F_X as closely as possible by taking appropriate values for the parameters γ, δ, λ, and ξ. Johnson defined 3 such systems that are capable of describing a wide variety of continuous populations--

1. The lognormal system S_L: $Z = \gamma + \delta \ln(X-\xi)$ $(X>\xi)$. (5)

2. The unbounded system S_U:

$$Z = \gamma + \delta \cdot \ln((X-\xi)/\lambda + \{[(X-\xi)/\lambda]^2 + 1\}^{1/2}) \quad (-\infty < X < \infty). \tag{6}$$

3. The unbounded system S_B:

$$Z = \gamma + \delta \ln[(X-\xi)/(\xi+\lambda-X)] \quad (\xi < X < \xi+\lambda). \tag{7}$$

For completeness Johnson [9] also defined

4. The normal system S_N: $Z = \gamma + \delta \cdot X$ $(-\infty < X < \infty)$. (8)

If the distribution F_X has the known moments

$$\mu_1' \equiv E[X];\ \mu_k \equiv E[(X-\mu_1')^k], \quad 2 \leq k \leq 4, \tag{9}$$

then in principle we can identify the appropriate function $f(\cdot)$ and evaluate all necessary parameters exactly (that is, to the limits of machine accuracy). In terms of the skewness and kurtosis

$$\beta_1 \equiv \mu_3^2/\mu_2^3 \quad \text{and} \quad \beta_2 \equiv \mu_4/\mu_2^2 \tag{10}$$

respectively, Figure 3 shows that Johnson's translation systems can accomodate all possible points in the (β_1, β_2) plane.

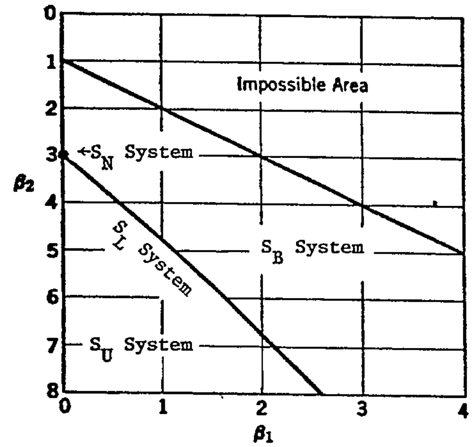

FIGURE 3. Chart for determining the appropriate Johnson system.

Generally β_1 and β_2 determine the functional form $f(\cdot)$, as well as the shape parameters γ and δ; then in terms of the auxiliary variate
$Y \equiv f^{-1}\{\exp[(Z-\gamma)/\delta]\} = (X-\xi)/\lambda$, we obtain the scale parameter $\lambda = [\mathrm{Var}(X)/\mathrm{Var}(Y)]^{1/2}$ and the location parameter $\xi = E[X] - \lambda \cdot E[Y]$.

When the only available information about F_X is contained in a random sample $\{x_j : 1 \leq j \leq n\}$ taken from this distribution, the usual procedure is to fit a Johnson curve to the sample data by either the method of moments [8,14,15,16,17,18] or the method of percentiles [8, 19, 20, 21, 28]. All of these schemes can yield parameter estimates that are infeasible in the following sense:

$$\hat{\xi} > \min\{x_j\} \quad \text{or} \quad \hat{\xi} + \hat{\lambda} < \max\{x_j\}. \tag{11}$$

As a basic principle of our research, we sought to develop univariate curve-fitting procedures that are guaranteed to avoid such anomalies. In fact, condition (11) prevents the use of the multivariate curve-fitting procedure discussed in the next subsection; see the remark following step 2 of that procedure. To avoid infeasible parameter estimates when fitting Johnson curves and to take advantage of the extra information available when one endpoint is known, we developed a general percentile-matching procedure using a Newton-Raphson method [22] that has been modified so that the step length is reduced whenever necessary to keep the latest trial solution within the feasible region that is the complement of (11).

A Procedure for Fitting Multivariate Johnson Distributions

Let $\underset{\sim}{X} = [X_1, X_2, X_3]'$ denote a continuous random vector having the (unknown) distribution function $F_{\underset{\sim}{X}}(x_1,x_2,x_3) = \Pr\{X_1 \leq x_1, X_2 \leq x_2, X_3 \leq x_3\}$. In [2] we prove the existence of a transformation $\underset{\sim}{T}$ that is one-to-one on the space of $\underset{\sim}{X}$ and that yields

$$\mathbf{Z} = \boldsymbol{\tau}(\mathbf{X}) \sim N_3\left\{\begin{bmatrix}0\\0\\0\end{bmatrix}, \begin{bmatrix}1 & \rho_{12} & \rho_{13}\\ \rho_{12} & 1 & \rho_{23}\\ \rho_{13} & \rho_{23} & 1\end{bmatrix}\right\} \quad (12)$$

a standardized trivariate normal distribution; see also [23, Example II.8.5] and [24, Theorem 2.12]. We assume that an adequate approximation to the i^{th} coordinate function $\tau_i(\mathbf{X})$ can be obtained with one of Johnson's univariate translations [9]:

$$Z_i = \tau_i(\mathbf{X}) = \gamma_i + \delta_i \cdot f_i[(X_i - \xi_i)/\lambda_i],\ 1 \le i \le 3. \quad (13)$$

Thus if we are given a random sample $\{\mathbf{X}_j = [x_{1j}, x_{2j}, x_{3j}] : 1 \le j \le n\}$ from F_X, then a trivariate fitting procedure can be based on the following steps:

1. Fit a univariate Johnson curve to the data set $\{x_{ij} : 1 \le j \le n\}$ corresponding to the i^{th} coordinate $(1 \le i \le 3)$ so that the transformed values
$$z_{ij} = \hat{\gamma}_i + \hat{\delta}_i \cdot f_i[(x_{ij} - \hat{\xi}_i)/\hat{\lambda}_i], \quad 1 \le j \le n, \quad (14)$$
can be regarded as a random sample from Φ_1.

2. Compute the sample mean and variance for the i^{th} transformed coordinate $(1 \le i \le 3)$:
$$m_1'(z_i) = n^{-1}\sum_{j=1}^{n} z_{ij},\ m_2(z_i) = n^{-1}\sum_{j=1}^{n}[z_{ij} - m_1'(z_i)]^2. \quad (15)$$
(Note that if condition (11) were to occur for the i^{th} coordinate, then we could not compute the transformed values $\{z_{ij} : 1 \le j \le n\}$; and thus the multivariate fitting procedure would fail at this step.)

3. Complete the specification (12) of the fitted trivariate Johnson distribution by computing the sample correlations between all pairs of transformed coordinates:
$$\hat{\rho}_{hi} = n^{-1}\sum_{j=1}^{n}\frac{[z_{hj} - m_1'(z_h)]}{m_2^{1/2}(z_h)} \cdot \frac{[z_{ij} - m_1'(z_i)]}{m_2^{1/2}(z_i)},$$
$$1 \le h,i \le 3. \quad (16)$$

Evaluating the Fitted Trivariate Distribution Functions

Given the cutoff values x_1°, x_2°, and x_3° for the 3 numerical eligibility criteria, we seek to compute the probability of randomly selecting an individual from the target population whose corresponding attributes $\mathbf{X} = [X_1, X_2, X_3]$ satisfy the conditions $X_1 \le x_1^\circ$, $X_2 \le x_2^\circ$, and $X_3 > x_3^\circ$. The algorithm for evaluating the fitted trivariate distribution function uses the transformed cutoff values

$$z_i^\circ = \hat{\gamma}_i + \hat{\delta}_i \cdot f_i[(x_i^\circ - \hat{\xi}_i)/\hat{\lambda}_i],\ 1 \le i \le 3, \quad (17)$$

in the fundamental relation

$$\begin{aligned}\Pr\{X_1 \le x_1^\circ, X_2 \le x_2^\circ, X_3 > x_3^\circ\} &= \Pr\{Z_1 \le z_1^\circ, Z_2 \le z_2^\circ, Z_3 > z_3^\circ\}\\ &= \Pr\{Z_1 \le z_1^\circ, Z_2 \le z_2^\circ\} - \Pr\{Z_1 \le z_1^\circ, Z_2 \le z_2^\circ, Z_3 \le z_3^\circ\}\\ &\doteq \Phi_2(z_1^\circ, z_2^\circ; \hat{\rho}_{12}) - \Phi_3(z_1^\circ, z_2^\circ, z_3^\circ; \hat{\rho}_{12}, \hat{\rho}_{13}, \hat{\rho}_{23}). \quad (18)\end{aligned}$$

The IMSL routine MDBNOR [25] provides the standardized bivariate normal distribution Φ_2, and the ADSSIM function PHI3 provides the trivariate normal distribution Φ_3.

The computational procedure implemented in PHI3 is based on Steck's formulation of trivariate normal probabilities in terms of the S-function [26]:

$$S(z,a,b) = \frac{b}{2\pi}\int_0^1 \frac{\Phi_1[z\cdot(1+a^2+a^2b^2t^2)^{1/2}]}{(1+b^2t^2)\cdot(1+a^2+a^2b^2t^2)^{1/2}}\,dt,$$
$$-\infty \le z,a,b \le \infty. \quad (19)$$

For each year and for each service to be analyzed during interactive execution of ADSSIM, expression (19) must be evaluated 480 times. Initially we computed the S-function using the IMSL routine DCADRE [25]; this is a numerical quadrature algorithm based on cautious adaptive Romberg extrapolation [27]. Because the resulting interactive response times seemed to be too large, we developed a faster evaluation procedure based on a third-order Taylor of the expansion of the S-function with a tight bound on the remainder; thus DCADRE is invoked only when the estimated truncation error in the Taylor expansion exceeds 10^{-6}. This yielded a 40% reduction in the overall execution time for ADSSIM.

DISCUSSION

ADSSIM incorporates many features that are considered to be important for evaluating existing and proposed services. It is practicable in terms of data requirements, and it operates interactively to enhance user friendliness. This allows for rapid evaluation and sensitivity analysis, which often is critical when responding to queries from internal and/or external decision makers. Hard copies of the analysis contain all assumptions used, and they also echo the input data. This explicit declaration of assumptions and data contribute to the credibility of the analysis.

ADSSIM is unique in that it operates by disaggregating given demographic forecasts into enough detail to evaluate the cost and impact of services. This process requires an efficient and accurate method for fitting the trivariate distribution functions for income, resources, and functional need within each service region and each age cohort. The multivariate extension of Johnson's univariate translation systems proved to be appropriate for estimating these distribution functions.

The trivariate fitting routine requires a credible sample of income, resources, and functional need measures for the state population. When ADSSIM was being developed, such a sample was not available since there had been no previously defined need for these data. However, the TDHR participates in a biennial survey of the state population, and this survey could be used to collect the required data. For the purposes of validating ADSSIM, crude sample data were compiled from existing sources.

ADSSIM was designed by the simulation committee after extensive dialogue with analysts and key decision makers at the TDHR. In addition to developing the process flow, the committee members participated in constructing data files and in model validation and evaluation. This participation was considered to be essential for gaining acceptance, especially since ADSSIM was to be a springboard for other decision support systems at the TDHR.

ADSSIM can be fully implemented when the appropriate sample data have been collected. In the meantime, a univariate version of the model is being used extensively for analyzing legislative appropriation requests. Output from this version can be plotted in color to enhance the analysis. The apparent success in implementing the univariate version of ADSSIM augurs well for the more elaborate trivariate model. We expect that this new approach will have broad aplication for enhancing public policy analysis.

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