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PROSPECTIVE PAYMENT: A SIMULATION MODEL OF MANAGEMENT STRATEGIES

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A simulation model developed to evaluate the financial effects of different management policies to face Medicare's Prospective Payment System is presented. This payment system, enacted by the Tax Equity and Fiscal Responsibility Act (TEFRA) of 1982, limits Medicare's reimbursement per patient to a fixed amount depending on the patient's particular type of disease. The reimbursement is based on a set of Diagnosis Related Groups (DRGs), which categorizes patients into disease classifications. As a result, hospitals must make efficiency gains and managers must look for new ways to provide quality care while containing cost. SLAM was the simulation language of choice. The network and discrete event portions are described in detail. The approach used to select specific DRGs for the analysis, as well as the statistical models used, preparation of input data, simulation routines and results of two runs are presented to illustrate how policies are simulated and results interpreted.

MEDICARE'S PROSPECTIVE PAYMENT SYSTEM

The TEFRA legislation of 1982, which became effective in October of 1983, represents the federal government's most recent regulatory effort to curb health care costs. It allows Medicare to be a more prudent buyer of medical services by imposing limits on hospital and physician reimbursement. This rate setting through "prospective reimbursement" attempts to restrain increases in health care expenditures by establishing, prior to a hospital's fiscal year, limits on the reimbursement that a hospital will receive for its services. Traditional reimbursement methods have allowed many inefficiencies to be built into health care systems. Retrospective payment by insurance groups has enabled hospitals and physicians to cover the cost of inefficiencies by simply increasing charges. Under this policy, the providers are neither penalized for wastefulness nor rewarded for cost containment. In response to this, Medicare's prospective reimbursement has been designed to encourage cost containment. The reimbursement is based on a set of diagnosis related groups (DRGs), which is defined by Moore to be a "classification scheme which categorizes patients who are medically related with respect to diagnosis and treatment, and are statistically similar in their lengths of stay" [1]. Under TEFRA, a hospital will receive a fixed payment for each patient according to the patient's DRG, regardless of the hospital's expense (there are exceptions to this rule when the patient has an extremely long length of stay for a certain DRG). A number of states have had mandatory rate setting programs since the early 1970s and most evaluations coincide in that they are effective in reducing the rate of growth in health care costs [2]. Medicare's prospective reimbursement system is similar to New Jersey's DRG system, which has 467 DRGs and has been in operation since 1971. Since some of these DRGs are segregated according to the patient's age, only 356 of them are applicable to Medicare patients.

PROBLEM STATEMENT

The objective of this research is to develop a simulation model to project the financial effects of alternative management policies in hospital's total reimbursement. Prospective reimbursement has changed the management of health care because hospitals and physicians are no longer able to increase their revenue by increasing their billing charges. The services spent on Medicare patients in a given DRG are only reimbursed to a pre-determined limit; therefore, a hospital loses money if its cost of service for a given patient exceeds this limit and profits if the cost is contained below the limit. Obviously the intent of the legislation is to encourage cost containment through a more efficient operation. Since up to 85 percent of costs (other than personnel costs) in a hospital's budget are generated by physicians and only 15 percent of physicians account for about 80 percent of the resource consumption excesses [3], some hospitals may introduce new types of cost control policies in an attempt to influence the practices of physicians by monitoring excessive use of resources. Another strategy may be to monitor ancillary services, particularly radiology (X-rays account for six to ten percent of the nation's total health expenditure and a large proportion are unnecessary) [4]. A number of other possible responses have been discussed (not necessarily endorsed) in the literature. Some hospitals have tried to offset potential revenue losses by shifting them to non-Medicare patients or by obtaining greater revenue from non-patient care activities [5]. Other institutions have implemented computerized diagnosis reporting procedures designed to maximize revenue for multi-diagnoses cases [6]. Reductions in the quality and accessibility of services has also been mentioned [7]: In larger cities hospitals may try to specialize in some categories of medicine while drawing back from other areas which could be served by neighboring institutions. Worse, some hospitals may attempt to gain revenue by manipulation of admission procedures: Some potential outpatients may be treated as inpatients (the DRG rate does not apply to outpatients) or patients with multiple problems may be readmitted, to receive a multiple DRG payment. Note that some of these policies may eventually reduce future reimbursements since the average length of stay for a DRG will be reduced.

Simulation is a technique for developing a representation of an actual system in order to replicate or project the effects of certain changes to the system. Many times, direct experimentation with a system is either infeasible or involves great risk; simulation provides a numerical representation of the system which can be manipulated without risk. The results of modifications to the simulated system can be measured, and provide an indication of the actual effects of the modifications.

As indicated, hospitals may introduce a number of cost control strategies in response to DRG reimbursement.

It is believed that simulation can be a valuable tool in the evaluation of those strategies. In relation to case-mix management, a simulation can generate a certain mix of patients based on historical data, along with the expected amount of resources which they would consume. Then, different management policies can be interjected to limit the number of resources in a specific DRG, or to limit the number of admissions of patients with certain illnesses, and the net gain or loss in reimbursement can be calculated. This will give administrators an indication of which policies would be most worthwhile and provide them with a better defined basis of cooperation with physicians with respect to resource consumption.

MODEL DEVELOPMENT

The basic objective of this simulation is to generate cost per patient based on the expected DRG case mix for a hospital and introduce modifications, or policies, to the health care process in order to simulate the total financial effects of these policies. For a useful and accurate model, the expected costs should be generated by separate cost components; then, separate policies can be applied to each component. Selective admission policies or policies to reduce certain patients' length of stay could also be considered. Forecasted changes in patient case mix of total patient volume may also be introduced in the analysis. The simulation projects the net savings or losses which would result from the introduction of such policies and forecasts.

THE APPROACH

In 1983, the hospital in the study discharged 1,375 Medicare patients among a total of 6,098 patients which incurred in $13.5 million in charges and represented 403 DRGs. Obviously, not all of the DRGs had the same impact on the hospital's financial picture. Some of them, while of quite frequent occurrence, represented a very minor proportion of total costs. Others, while occurring quite infrequently, were so expensive that each occurrence turned out to be significant. It was decided to concentrate the analysis on those DRGs which contributed most to the hospital's total charges (hence, the total costs). An approach analogous to an industrial A-B-C inventory analysis was used [8]. By this process, managers focus attention to the few items which account for a great portion of the total costs. By exercising tight control over the "Class A" items, a great portion of the total volume can be controlled with relatively little effort.

When ranked in order of charges (see Table 1), the twenty highest DRGs accounted for 38.5% of the total charges. For Medicare patients, the twenty highest DRGs accounted for 46.2% of total charges. Hospital managers should concentrate attention in "Class A" DRGs, which is recommended to include the top twenty or twenty-five DRGs (e.g., those accounting for the larger share of costs). Data availability and nature of illness are also determinant in the selection of DRGs to include in the analysis. Other important considerations would be: a) Are there enough cases within each DRG to build a statistically sound model?; b) Since Medicare patients are the only patients which provide a restricted reimbursement, does the hospital want to concentrate only on DRG's which have had a considerable number of Medicare patients?; c) Can hospital managers practically enforce cost containment policies whithin a certain DRG? For example, a DRG which involves major surgery would be generally not a good target for cost containment policies; and d) Can admissions policies be enforced for a particular DRG? Only hospitals in or near major cities would be able to effectively refer patients to other institutions.

TABLE 1: A-B-C ANALYSIS

January-December 1983: Total Charges = $13,507,221

Rank	DRG #	% Tot. Charges	Cumul. Percent	N of Pts	Med Pts
1	373	3.80	3.80	589	0
2	468	3.35	7.15	67	25
3	243	3.08	10.23	143	143
4	355	3.07	13.30	170	5
5	122	2.61	15.91	77	35
6	371	2.59	18.50	177	0
7	14	2.30	20.80	60	52
8	127	2.16	22.96	85	63
9	148	2.07	25.03	27	19
10	210	1.76	26.79	26	22
11	391	1.67	28.46	677	0
12	140	1.46	29.92	96	49
13	209	1.30	31.22	19	16
14	96	1.20	32.42	45	31
15	89	1.15	33.57	35	22
16	182	1.12	34.69	75	44
17	121	1.05	35.74	29	14
18	82	1.00	36.74	37	21
19	183	0.86	37.60	83	11
20	202	0.86	38.46	21	3

Several costs are generated in the treatment of a patient. The hospital which contributed data to perform this research has segregated its costs into the following cost centers:

Laboratory	Medical Supplies
Pharmacy	Nuclear Medicine
Radiology	Respiratory Therapy
Scanner	EEG-EKG-Cardiology
ICU	Delivery Room
Blood	Rehabilitation
Emergency Room	Misc. ancill. cost
Operating Room	Semi-private room
Recovery Room	Misc. room costs
Anesthesia	Physical Therapy

For each DRG, the expected value of the expense from each cost categories was derived from historical data, available through the hospital's management information system. Individual patient billing data specifies the length of stay and the amount charged for patient care within each cost center. With this information, the average charge and variance of charges can be derived. A Resource Consumption Report was available through the hospital's DRG information system.

TABLE 2: DRGs SELECTED FOR ANALYSIS

DRG 468:	Unrelated operations procedure (7 cases)
DRG 14:	Specific cerebrovascular disorders except transient ischemic attacks (16)
DRG 127:	Heart failure and shock (34)
DRG 148:	Major small and large bowel procedures age>69 and/or complic. or comorbidity (8)
DRG 210:	Hip and femur procedures except major joint age>69 and/or complications (15)
DRG 243:	Medical back problems (26)
DRG 999:	Other (52 cases)

For the purpose of illustrating the proposed approach, six DRGs were selected. They are listed in Table 2, with the sample cases used. These DRGs represent a wide range of statistical situations to consider for a simulation. DRG 999 incorporates all other DRGs which are not specified (a random sample was taken of every tenth patient which was assigned a DRG other than the ones selected for in-depth analysis).

PREPARATION OD INPUT DATA

The flow of patients through the hospital is simulated as follows: Patients "arrive" and are assigned certain attributes (DRG, LOS, and resource consumptions). These attributes are generated by random variables with distributions that fit the frequency distribution of the actual data [9]. For example a hospital's cost per case is generally "skewed rightward" which implies a lognormally or exponentially shaped distribution. That is, most cases have a relatively small cost, however a few cases have very large cost. The average value and variance of the cost for such a distribution can, therefore, be used to generate costs in the simulation. The attributes which cannot be fitted to a theoretical distribution are generated empirically using a triangular distribution [10]. There are three parameters required for a triangular distribution: the minimum, the mode, and the maximum. If there was no single mode, the mid-point of the most frequent interval in the histogram was used [11].

The DRG grouping system segregates patients into meaningful categories for statistical analysis. Historical records of length of stay and resource consumption were used to construct mathematical model and distributions to simulate the financial process of health care delivery. Figure 1 is an example of the statistical analysis carried on the length of stay (LOS) for DRG 127. A lognormal distribution with a mean of 6.7 and a standard deviation of 6.3 days was hypothesized. Goodness of fit tests were performed to substantiate all hypotheses.

```
  Mid   Freq.   (An * equals approximately
 point           0.40 occurrences)

    2     5    *************
    4    11    ******************
    6     9    *********************
    8     1    ***
   10     2    *****
   12     2    *****
   14     1    ***
   16     1    ***
   18     0
   20     0
   22     0
   24     0
   26     1    ***
   28     0
   30     1    ***
               I....+....I....+....I....+....I.
               0         4         8        12

                 Histogram Frequency

      Mean    6.706    Std. Dev.   6.345
      Mode    4.000    Std. Err.   1.088
      Median  5.000    Variance   40.275
      Cases   34
```

Figure 1: LOS Histogram, DRG 127

The length of stay is the primary controlling variable that determines the amount of resources which are consumed by a patient. Of course, there are those patients which have a shorter lehgth of stay than others, yet a greater amount of resource consumption. However, by examining patients within each DRG, the number and extend of these variations can be greatly reduced. Also, by considering intensive care stay and regular room stay separately, certain variations can be expected, since the rate at which intensive care patients use resources is generally greater than that of patients under regular care. Furthermore, by examining each component of cost, an account for certain variation can be made. For example, emergency room costs are obviously independent from a patient's length of stay, since these costs are generally fixed and are incurred before the patient begins rooming in the hospital.

The next step is to test theoretical distributions to be used to generate LOS in the simulation. The chi-square goodness of fit test was chosen to evaluate the theoretical distribution against the actual distribution of values. Since most DRG's had LOS histograms that were lognormally-shaped, the lognormal distribution was chosen for evaluation, using the parameters of the sample from the observed data. In order to test this hypothesis, it was necessary to examine the distribution of the natural log of LOS. A chi- square test was performed to test for normality of LOGLOS within each DRG. There was one DRG for which the variable did not pass the chi-square test, and two for which there was insufficient data to perform the test. For these DRG's, it was determined that a triangular distribution be used for the generation of LOS. Table 3 presents the results and distributions used to generate LOS for each DRG. It is worthwhile to note that the DRG's for which the lognormal distribution could not be assigned were also the ones with the smallest sample size. It is believed that a larger sample may indicate that LOS was also lognormally distributed for these DRGs. Furthermore, in the absence of data, an experienced practioner will be able to estimate the minumum, maximum and most likely length of stay for any specific disease. It may even be advantageous to use these parameters as opposed to ones derived from only a few pieces of data.

TABLE 3: LOS DISTRIBUTIONS SELECTED

DRG	Lognormal (mean, st.dev.)		Triangular (min,mode,max)		
468	—	—	2	8	24
14	13.82	13.53	–	–	–
127	6.60	5.93	–	–	–
148	—	—	9	12	29
210	—	—	5	21	32
243	9.89	7.17	–	–	–
999	8.45	7.73	–	–	–

Table 4 includes parameters incorporating the proportion of intensive care days for each DRG. P(0) represents the probability that for a given DRG only a regular room is needed, P(1) that of needing just an Intensive Care room. If neither case applies, the proportion of ICU days was generated with a triangular distribution whose parameters were empirically determined.

The analysis of length of stay is independent of other variables; however, for the resource consumption analysis, it is determined if definite relationships exist between the expected amount of resources used by a patient and the length of stay of the patient. These relationships are used in the simulation to generate resource consumption as a function of the patient's length of stay and type of room occupied.

TABLE 4: GENERATION OF % ICU DAYS

DRG	P(Ø)	P(1)	Cases Ø<%<1	Triang. Distr.		
468	Ø.86	Ø.ØØ	1	Ø.Ø6	Ø.Ø6	Ø.Ø6
14	Ø.44	Ø.13	7	Ø.18	Ø.23	Ø.59
127	Ø.44	Ø.Ø9	16	Ø.1Ø	Ø.5Ø	Ø.67
148	Ø.63	Ø.ØØ	3	Ø.2Ø	Ø.24	Ø.46
21Ø	Ø.8Ø	Ø.ØØ	3	Ø.Ø5	Ø.Ø6	Ø.Ø9
243	Ø.96	Ø.ØØ	1	Ø.Ø4	Ø.Ø4	Ø.Ø4
999	Ø.75	Ø.Ø6	1Ø	Ø.Ø8	Ø.4Ø	Ø.6Ø

In this model, costs are determined by generating the charge from each department (since the charge data is available) and multiplying this charge by the cost-to-charge ratio of that department (also available). These products are accumulated to obtain a total cost for the patient. After the model has been verified, the hospital policies to be simulated can be logically introduced within the code of the simulation.

Due to the fact that, for many cases, costs were incurred in only a few cost centers, the resource consumption analysis focuses attention on certain cost centers. Regression analyses were performed to approximate the total cost to the patient as a linear function of five cost centers: lab, pharmacy, supplies, respiratory therapy and radiology. These centers were chosen because they were the most frequently used and had the greater contribution to total cost. Not all centers are significant for all DRGs. As can be seen in Table 5, very high multiple regression coefficients were found within each DRG.

Another series of fitting models were run to determine relationship between costs incurred in each center and length of stay. In general it was hypothesized that departmental charges were lognormally distributed. This is consistent with the statement by Grimaldi and Micheletti that resource consumption distribution are generally "skewed righward". When the hypotheses were rejected, triangular distributions were fitted.

All of these regression models are used in the simulation to estimate total hospital cost as a function of charges from the five centers. Although this analysis deals only with hospital charges (costs to the patient), the models are also used to approximate hospital costs. This is due to the fact that the hospital's departmental costs are estimated as direct proportions of the charges via the observed cost-to- charge ratios from each department. That is, the charge from each department is multiplied by the cost-to-charge ratio, then entered into the regression model to approximate the total hospital cost for each patient.

A summary of the distribution type and parameters for department charges is in Table 6. Again, for generation of the distributions, the probability that the departmental charges equal zero (P[Ø]) was introduced.

Initial test runs of the simulation revealed that the departmental charge regression equations were valid for only a certain range of length of stay values. Specifically, when a patient's length of stay exceeded the maximum length of stay from the three-month data base, or fell below the minimum observed value,

TABLE 5: COEFFICIENTS OF REGRESSION EQUATION

TCOST = A + B*LAB + C*PHARM + D*SUPP + E*RETHER + F*XRAY

Coefficients of Determination are also given

DRG	A	B	C	D	E	F	R2
468	369.69	8.44	3.69	Ø.ØØ	Ø.ØØ	Ø.ØØ	Ø.99
14	-134.12	1Ø.89	2.94	Ø.ØØ	Ø.ØØ	Ø.ØØ	Ø.97
127	6ØØ.ØØ	2.41	3.Ø8	Ø.ØØ	2.23	Ø.ØØ	Ø.99
148	3238.49	7.98	Ø.ØØ	1.82	Ø.ØØ	Ø.ØØ	Ø.98
21Ø	2941.31	5.14	Ø.ØØ	2.52	3.81	Ø.ØØ	Ø.94
243	5Ø7.9Ø	Ø.ØØ	2.38	Ø.ØØ	Ø.67	Ø.ØØ	Ø.97
999	274.67	1.Ø6	Ø.69	2.Ø6	1.15	1.38	Ø.89

extremely large or even negative charges were frequently generated. An algorithm was develop to produce realistic results. In cases were the generated charges fell outside the observed range of charges, a linear aproximation was subtituted for the regression models. In practice the maximum length of stay from several patients samples correlates reasonable well with maximum departmental charges from those samples. Thus, the algorithm incorporates the proportional relationtionship of charges to length of stay.

It is concluded that the three types of mathematical models implemented in this simulation (the lognormal distribution, the triangular distribution and regression equations) are sufficient for a complete and accurate generation of patient attributes.

THE SIMULATION

SLAM II (Simulation Language for Alternative Modeling), was the language chosen in this research [12]. Although the flow of simulation logic is unique to this software, the modeling principles can be applied with any language. The statistical analysis was done with SPSS, Statistical Package for the Social Sciences [13]. All these programs were run in an IBM 4381 computer

SLAM is a FORTRAN-based language which incorporates network modeling with optional discrete event modeling. The network portion displays certain events, represented by nodes, encountered by an entity (patient), and activities through which the entity passes, represented by arrows. Events include the arrival of a patient, DRG assignment, entrance into a queue (room, X-ray, lab, etc.), and departure from the system. Typical activities includes services performed for the entity and other time-dependent processes, as well as conditional branching to different events. The discrete event section provides for computation of detailed or complicated routines such as the generation of length of stay and resource consumption for each patient. SLAM automatically collects statistics for length of stay, costs, and profit analyses. Separate statistics are kept for non-Medicare patients.

TABLE 6

CHI-SQUARE TEST RESULTS AND DEPARTMENT CHARGE DISTRIBUTION BY DRG FOR CHARGES NOT GENERATED FROM REGRESSION EQUATIONS

Department	DRG	P[Ø]	No. Patients in Sample	X^2_o	$X^2_{o,K-3}$	Hypothetical Distribution Type: T-Triangular L-Lognormal	For Lognormal Distribution: μ_x, σ_x (Calculated From $\bar{Y}$, SY)	For Triangular Distribution: Min, Mode, Max
LAB	14	0	16	2.81	3.84	L	375.2, 423.9	-
	210	0	15	0.36	3.84	L	452.7, 230.4	-
	243	0	26	0.27	5.99	L	188.7, 124.2	-
	999	0	52	0.87	7.81	L	347.7, 252.1	-
PHARM	148	0	8	--	--	T	-	1055.2, 1755.2, 6909.6
	999	0	52	6.56	7.81	L	480.1, 725.1	-
SUPP	210	0	15	1.37	3.84	L	1284.4,1003.0	-
RETHER	127	0.21	27	0.18	5.99	L	685.4, 884.4	-
	148	0.25	6	--	--	T	-	21.8, 321.8, 9335.1
	210	0.47	8	--	--	T	-	29.0, 129.0, 763.2
	999	0.46	28	2.03	5.99	L	577.4,1358.1	-
XRAY	14	0.19	13	--	--	T	-	41.0, 41.0, 536.0
	127	0.03	33	--	5.99	L	131.6, 71.8	-
	148	0	8	--	--	T	-	45.0, 45.0, 773.0
	210	0	15	--	--	T	-	241.0, 391.0, 589.0
	243	0.12	23	0.10	5.99	L	169.8, 127.8	-
	468	0.29	5	--	--	T	-	64.0, 114.0, 220.0
	999	0.08	48	2.95	7.81	L	160.0, 127.2	-

THE NETWORK PORTION OF THE SIMULATION

The SLAM network portion is used to assign a DRG number to an arriving patient and to collect statistics for each patient after the length of stay and resource consumption variables have been generated in the FORTRAN subroutine. The network is presented in Figure 2 and depicts the probabilistic branching required for assigning DRG's and collecting various statistics.

The first node on the left side of the network is the CREATE node where patients are generated according to the parameters specified by the node (interarrival time, the attribute mark number, and the maximum number of branches which can be taken upon completion of the CREATE routine). Then each patient is assigned a DRG code based on the actual 1983 case mix. The branches emanating from the CREATE node have associated probabilities which are equal to the observed proportions of the occurrence of each DRG in 1983. This is were forecasts of case-mix chages can be introduced. For example, if the hospital expects a great influx of elderly population into their community, the increased proportion of patients in particular DRGs can be reflected.

After assignment of a DRG number, the EVENT node calls the FORTRAN discrete-event subroutine. This subroutine generates all of the length of stay and resources consumption values for each patient based on the results of the analysis of data. The attributes used for each variable in this subroutine are defined in Table 7

After returning from the discrete-event portion, statistics are collected separately for Medicare and non-Medicare patients. For medicare patients, the outlier flag is collected for all patients and per DRG (the averaged value will be the percentage of outliers). Cost and profit statistics are also collected. For all patients, departmental costs are collected along with total cost and profit.

TABLE 7

POSITIONS FOR PATIENT ATTRIBUTES

ATRIB Array Positions	Description of Attribute (Variable Name in Prenthesis)
1	Time of Arrival
2	DRG code (1 through 7) (ID)
3	Total Length os Stay (LOSTOT)
4	Length of Stay in Regular Room (LOSREG)
5	Length of Stay in ICU (LOSICU)
6	Medicare Flag (Ø = non-Medicare, 1= Medicare)
7	Outlier Flag (Ø = non-outlier, 1 = outlier)
8	Hospital's Total Cost (TCOST)
9	Reimbursement to Hospital (PAY)
1Ø	Profit [ATRIB(9) - ATRIB(8)]
11	Laboratory Cost
12	Pharmacy Cost
13	Supply Cost
14	Respiratory Therapy Cost
15	Radiology Cost

The SLAM program code for the simulation is presented in Figure 4.

THE DISCRETE-EVENT PORTION OF THE MODEL

This FORTRAN subroutine is the heart of the patient flow model. The functional flowchart diagram is shown in Figure 3. The diagram shows where interjection of new policies are made. All of the results of the data analysis are incorporated in this routine to generate length of stay, resource consumption and total cost for each patient. The results of the data analysis are assigned to several array variables. For example, the positions within XLOS(DRG,J) are defined for cell number J as indicated in Table 8.

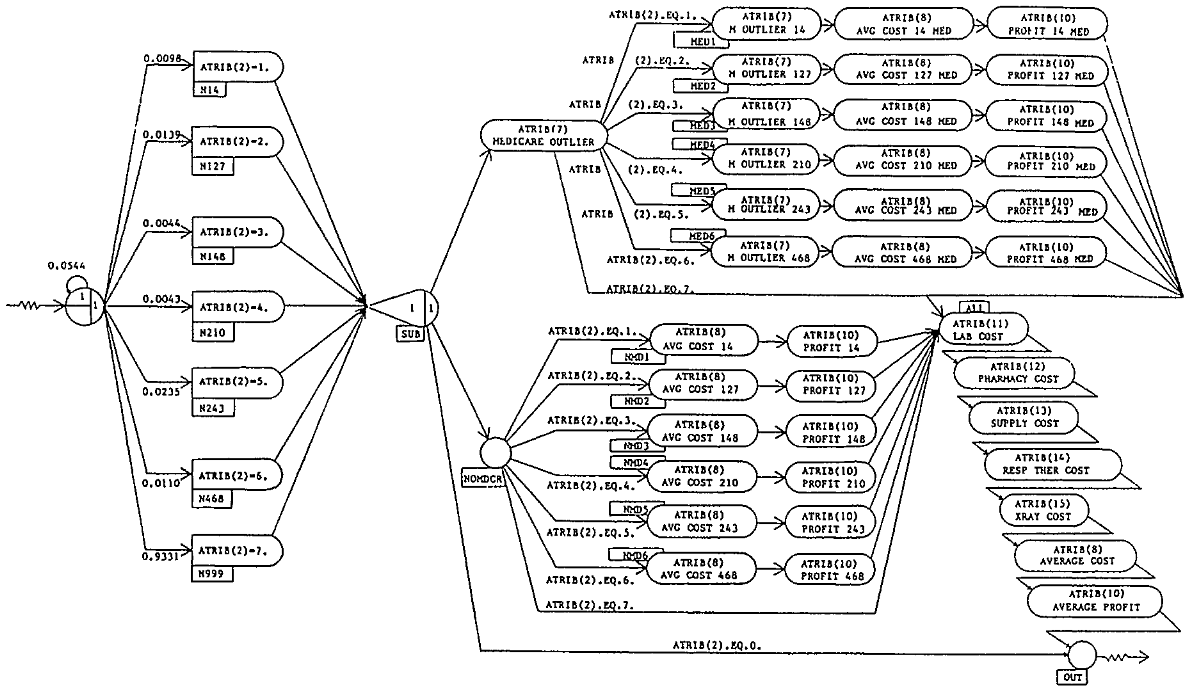

Fig. 2. SLAM network for patient cost simulation.

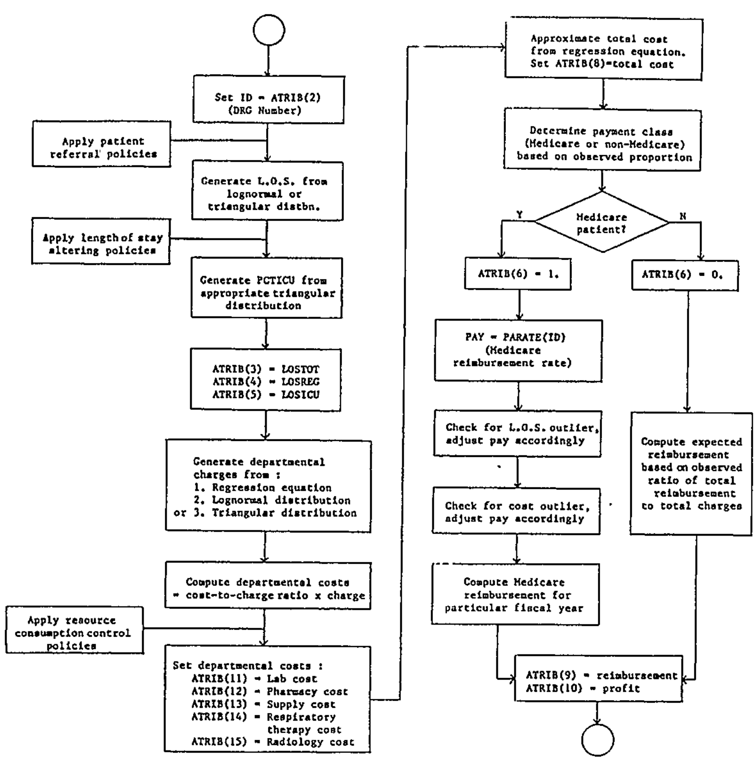

Fig. 3. Functional flowchart for subroutine EVENT.

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GEN,J. SEPULVEDA, PATIENTS, 2/21/85;
LIM,1,15,5Ø;
INIT,Ø,365.;
NETWORK;
        CREATE,Ø.Ø544,,1,,1;
        ACTIVITY,,Ø.ØØ98,N14;
        ACTIVITY,,Ø.Ø139,N127;
        ACTIVITY,,Ø.ØØ44,N148;
        ACTIVITY,,Ø.ØØ43,N21Ø;
        ACTIVITY,,Ø.Ø235,N243;
        ACTIVITY,,Ø.Ø11Ø,N468;
        ACTIVITY,,Ø.9331,N999;
N14     ASSIGN,ATRIB(2)=1.;
        ACT,,,SUB;
N127    ASSIGN,ATRIB(2)=2.;
        ACT,,,SUB;
N148    ASSIGN,ATRIB(2)=3.;
        ACT,,,SUB;
N21Ø    ASSIGN,ATRIB(2)=4.;
        ACT,,,SUB;
N243    ASSIGN,ATRIB(2)=5.;
        ACT,,,SUB;
N468    ASSIGN,ATRIB(2)=6.;
        ACT,,,SUB;
N999    ASSIGN,ATRIB(2)=7.;
SUB     EVENT,1,1;
        ACT,,ATRIB(2).EQ.Ø.,OUT;
        ACT,,ATRIB(6).EQ.Ø.,NOMEDCR;
        ACT,,ATRIB(6).EQ.1.;
        COLCT,ATRIB(7),MEDICARE OUTLIER;
        ACT,,ATRIB(2).EQ.1.,MED1;
        ACT,,ATRIB(2).EQ.2.,MED2;
        ACT,,ATRIB(2).EQ.3.,MED2;
        ACT,,ATRIB(2).EQ.4.,MED4;
        ACT,,ATRIB(2).EQ.5.,MED5;
        ACT,,ATRIB(2).EQ.6.,MED6;
        ACT,,ATRIB(2).EQ.7.,ALL;
MED1    COLCT,ATRIB(7),M OUTLIER 14;
        COLCT,ATRIB(8),AVG COST 14 MED;
        COLCT,ATRIB(1Ø),PROFIT 14 MED;
        ACT,,ALL;
MED2    COLCT,ATRIB(7),M OUTLIER 127;
        COLCT,ATRIB(8),AVG COST 127 MED;
        COLCT,ATRIB(1Ø),PROFIT 127 MED;
        ACT,,ALL;
MED3    COLCT,ATRIB(7),M OUTLIER 148;
        COLCT,ATRIB(8),AVG COST 148 MED;
        COLCT,ATRIB(1Ø),PROFIT 148 MED;
        ACT,,ALL;
MED4    COLCT,ATRIB(7),M OUTLIER 21Ø;
        COLCT,ATRIB(8),AVG COST 21Ø MED;
        COLCT,ATRIB(1Ø),PROFIT 21Ø MED;
        ACT,,ALL;
MED5    COLCT,ATRIB(7),M OUTLIER 243;
        COLCT,ATRIB(8),AVG COST 243 MED;
        COLCT,ATRIB(1Ø),PROFIT 243 MED;
        ACT,,ALL;
MED6    COLCT,ATRIB(7),M OUTLIER 468 MED;
        COLCT,ATRIB(8),AVG COST 468 MED;
        COLCT,ATRIB(1Ø),PROFIT 468 MED;
        ACT,,ALL;
NOMDCR  GOON;
        ACT,,ATRIB(2).EQ.1.,NMD1;
        ACT,,ATRIB(2).EQ.2.,NMD2;
        ACT,,ATRIB(2).EQ.3.,NMD2;
        ACT,,ATRIB(2).EQ.4.,NMD4;
        ACT,,ATRIB(2).EQ.5.,NMD5;
        ACT,,ATRIB(2).EQ.6.,NMD6;
        ACT,,ATRIB(2).EQ.7.,ALL;
NMD1    COLCT,ATRIB(8),AVG COST 14;
        COLCT,ATRIB(1Ø),PROFIT 14;
        ACT,,,ALL;
NMD2    COLCT,ATRIB(8),AVG COST 127;
        COLCT,ATRIB(1Ø),PROFIT 127;
        ACT,,,ALL;
NMD3    COLCT,ATRIB(8),AVG COST 21Ø;
        COLCT,ATRIB(1Ø),PROFIT 21Ø;
        ACT,,,ALL;
NMD4    COLCT,ATRIB(8),AVG COST 148;
        COLCT,ATRIB(1Ø),PROFIT 148;
        ACT,,,ALL;
NMD5    COLCT,ATRIB(8),AVG COST 243;
        COLCT,ATRIB(1Ø),PROFIT 243;
        ACT,,,ALL;
NMD6    COLCT,ATRIB(8),AVG COST 468;
        COLCT,ATRIB(1Ø),PROFIT 468;
ALL     COLCT,ATRIB(11),LAB COST;
        COLCT,ATRIB(12),PHARMACY COST;
        COLCT,ATRIB(13),SUPPLY COST;
        COLCT,ATRIB(14),RESP THER COST;
        COLCT,ATRIB(15),XRAY COST;
        COLCT,ATRIB(8),AVERAGE COST;
        COLCT,ATRIB(1Ø),PROFIT;
OUT     TERMINATE;
        END;
FIN;
```

Figure 4: SLAM Program Listing for Patient Simulation

TABLE 8: THE LOS ARRAY DEFINITION

Description of Contents

1 If this value equals zero, it indicates that a lognormal ditribution will be used to generate LOS. Otherwise, a triangular distribution is used and the cell contains the maximum value parameter for the triangular distribution.

2 For a lognormal distribution, the theoretical mean of LOS; for a triangular distribution, the mode parameter.

3 For a lognormal distribution, the standard deviation of LOS; for a triangular distribution, the minimum value parameter.

4 The expected probability that Percent ICU equals zero.

5 The expected probability that Percent ICU equals one.

6 The minimum value parameter of the triangular distribution for Percent ICU.

7 The node parameter of the Percent ICU triangular distribution.

8 The maximum value parameter of the Percent ICU triangular distribution.

VALIDATION

To validate the model, several performance measures were compared to the real values. Table 9 shows the comparison of simulated average departmental costs and actual costs. The reason for the large over approximation in the supply and respiratory therapy departments is that the distributions used in this generation (in particular the triangular distribution) may not be representative of actual data. It is believed that a larger data base would decrease the magnitude of errors in the simulated costs, since there would be enough data points to attempt to find a better fitting distribution.

TABLE 9

COMPARISON OF SIMULATED AVERAGE DEPARTMENTAL COSTS VS ACTUAL COSTS

Department	Actual ($)	Simulated ($)	Error (%)
Lab	247.Ø	245.2	Ø.7
Pharmacy	184.6	192.4	4.2
Supplies	178.4	2Ø9.8	17.6
Resp. Ther.	123.7	148.5	2Ø.Ø
Radiology	98.9	98.6	Ø.3

To further validate the model, the costs per DRGs were compared. Table 1Ø presents the comparison which indicates a very accurate model for most DRGs. The large error for DRG 148 is attributed to small sample size. DRG 999 (all others) is unlikely to represent the population.

TABLE 1Ø

COMPARISON OF THE AVERAGE COST PER PATIENT BY DGR

DRG	Actual ($)	Simulated ($)	Error (%)
14	1698.6	1699.Ø	Ø.Ø
127	996.Ø	971.Ø	2.5
148	4336.8	5687.Ø	31.1
21Ø	2673.5	27Ø6.Ø	1.2
243	1479.6	1426.Ø	4.2
468	696.3	755.6	8.5
999	118Ø.7	1379.Ø	16.7

It is concluded that the simulation model provides an acceptable representation of the real system. It is believed that the simulation would be very accurate if more data (in sample size and over a longer period of time) would have been available (not done due to funding problems).

INTERJECTION OF POLICIES

This simulation is capable of predicting the effects of many types of alterations to the system. For the purposes of illustration, two management policies were introduced. The summary report from these simulations are given in Table 11

TABLE 11: SUMMARY OF RESULTS

Profit Increase with respect to Baseline

	Strategy 1 $	Strategy 1 %	Strategy 2 $	Strategy 2 %
DRG 14	Ø	(Ø.ØØ)	42	(Ø.94)
DRG 21Ø	66	(1.14)	Ø	(Ø.ØØ)
Radiology	9.9Ø	(1Ø.Ø4)	Ø	(Ø.ØØ)
All Cases	1.3Ø	(Ø.Ø3)	7.8Ø	(Ø.83)

The first policy was that of decreasing the costs incurred in the radiology department by ten percent. Average profit is $944.4. With no policy, the average profit was $941.1. The simulation indicates that a ten percent increase in efficiency for the radiology department would result in a net gain on the order of $2,ØØØ (6718*Ø.3). It can be seen that this policy has an impact on DRG 21Ø cases (average profit increases by $66 per case). DRG 14 is not sensitive to this policy while Radiology is, as it was expected.

The second policy is that of extending the length of stay of patients whose stay approaches the outlier trim point. This policy was attempted under the assumption that outliers (Medicare and non-Medicare combined) are profitable to hospitals. The patient's length of stay was extended by two days if the length of stay was within two days of the trim point. Compared to the profit with no policy, indications are that this policy would be desirable if it could be practically enforced.

These two examples illustrate how simulation can be viable tool in the selection and enforcement of certain hospital management strategies, as well as predicting results of forecasts for planning purposes. Although this research is not comprehensive in its scope, it is believed that further investigation in this area will produce a lasting contribution which could help to support hospital planning and decision making.

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