Forecasting Health Care Expenditures and Utilization based on a Markov Process and a Deterministic Cost Function in Managed Care Settings

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This study is exploratory in nature with a goal of extending the application of stochastic modeling to health economics research. The aim of this study is to investigate whether the prediction of utilization and attendant costs through the development of a stochastic model, specifically a first-order Markov chain, can be adapted to specific diseases and/or events. The original study considered three diseases. They included both chronic and acute diseases. The choices were diabetes, hypertension and myocardial infarction. For the purposes of this article the application is illustrated by looking at the group with hypertension. The group of $n = 1019$ was randomly split into two groups. They were then categorized into age groups {over 66/under 66} and gender {male/female}. The first group was used to generate the transition probabilities and second was used to validate the results. Chi-square analysis was performed and there were no significant differences between the groups. The costs were computed and presented.

1. Introduction. Predicting cost in the health care environment is a challenging dilemma for medical professionals. The importance of a viable cost model incorporating outcomes measurement and payment schemes is of interest [16, 10, 17]. Healthcare administrators want to assure that the delivery of services is appropriate as identified by federal government guidelines, rules and regulations [22]. A critical starting point is to provide the framework necessary to provide a cost model that considers the general factors of healthcare encounters, patient diagnosis, treatment and the related costs that can be used to describe this complex problem. The very stochastic nature of disease treatment can lead to substantial variation in experience between and among classes of enrollees, their diseases, and treatment utilization patterns [20]. The most common approach to analyzing "cost of disease" is the "traditional method" of summing the number of events occurring in the system over a period of time and calculating the mean and a standard deviation of cost [9]. There is a need for more sophisticated models to predict cost in the health care environment. A wide variety of conceptual and statistical models exist, both deterministic and stochastic, to measure utilization in health research [9]. The deterministic models are "traditional model" (summing of events), and decision analysis (decision tree). The limitation of the "traditional model" is its inability to account for the skewness of cost data. Decision trees can be effective models in economic and policy analyses, because they can provide information to patients and practitioners about risk and cost. The difficulties with this model arise when timing becomes a concern. This problem becomes apparent when the time interval is several years or there are repeated events in a shorter time interval. Unfortunately, the longer the time period for events to occur can lead to more noise or numerous branches in the decision tree and that makes it unmanageable or practical. The limitations for the deterministic models are an inability to account for the non-symmetric aspect of cost data and the lack of consideration of the utilization patterns of the population [18].

2. Specific Aims. This study used real and frequently used criteria for cost: allowable reimbursement for the services. The particular criteria are based on Heath Care Financing Agency (HFCA) reimbursements [21]. There are several obvious practical advantages of using a Markov process. The first advantage of the Markov Model is its ability to be used as a flexible general model that can be applied in different settings by using the utilization pattern and allowing the cost change geographically. The Markov process has the ability to measure the randomness of the utilization pattern of any given population [3]. Another potential gain of this technique is its ability to model the utilization process into "compartments" that capture the actual medical care delivery process. Developing a cost model based on combining a Markov process and the corresponding fixed costs associated with this utilization has ample justification. This study treats actual cost as deterministic. This assumption is valid as cost reimbursement schedules have little or no significant variation. In fact with health care constraints in place, the health-care providers have a relatively narrow band for compensation and adjust their costs accordingly [21].

3. Background and Motivation. The Markov process has been used extensively in the modeling of epidemics- progression, risk of spread [3]. The epidemics modeled by the Markov process in literature range from the influenza [2], tuberculosis [5] to HIV [1, 23]. The application of Markov processes to today's challenging health-care problems is widespread [3, 6, 11, 7]. All of the above studies used a Markov chain as the underlying mechanism to model the pathways for subjects to predict utilization or possible pathways through the healthcare system.

The Markov process has been used to predict utilization in various healthcare plans and healthcare systems. Kapadia *et al.* [12] studied 305 patients at a 90-bed comprehensive rehabilitation hospital in a major metropolitan area over a six-month period, January – July, 1982. The authors used hospital service charges and diagnosis to measure the utilization patterns of the patients, Beland [4] studied ambulatory care in Montreal, Canada. The sample consisted of 2149 patients. The author used the physician claims from clinic visits, hospitalization and emergency room visits. The author used a Markov chain to predict utilization to show the differences between population demographics - age and gender in the model and the corresponding changes in the traditional model of counting visits to physicians. Beland dichotomized the patients into those aged less than or equal to 64 years and those aged greater than or equal to 65 years. Beland broke the time period into 4-month periods. Beland found differences in utilization patterns based upon sex and age. The population was limited to people using ambulatory care. The resident

Table 1. The resident states for the Markov process

State 0	No use of services	m_0
State 1	PCP visits	m_1
State 2	Visiting a specialist	m_2
State 3	Hospital visits	m_3
State 4	Emergency Room visits	m_4
State 5	Outpatient Procedure	m_5
State 6	Outpatient Treatment and Radiology	m_6
State 7	Pathology	m_7
State 8	Termination from plan	m_8

states of the Markov process that Beland used formed a subset of the states that we use. The results of the above literature review indicate that the Markov process is appropriate to estimate the utilization of a population of patients or enrollees. The Markov process can illustrate the difference in the treatment utilization patterns due to predictor variables such as gender and age. None of the previously listed studies examine the question that this study attempts, but the application of a generalized Markov process seems appropriate to predict utilization for patients with chronic or acute diseases [15]. This study uses a comprehensive utilization pattern (nine resident transition states). The use of the Markov process provides an unbiased estimator of the treatment utilization pattern of the population that is being investigated.

4. Methods. The Markov process, which incorporates the stochastic element, is being employed as the first component of this model to predict utilization for this healthcare problem. The transition or change in utilization from state i to state j is influenced by the prior state. The notation is

$$P_{ij} = \Pr[X_{n+1} = j | X_n = i],$$

where P_{ij} is the probability of going from state i to state j in one step or one increment in the time unit. Due to the restraints of the utilization plan, there is no need to consider all the previous transitions. This is due to the restraints placed on the enrollees in a managed care plan. All the transitions from the resident states require preset exit criteria and only the previous state influences the opportunity for transition to an alternate state. This means that being in a resident utilization state two transitions earlier is irrelevant to the state you are in presently. All the information that is needed is the previous transition state. This is using the memory less or Markovian property [8]. The resident states of transition based on utilization for the Markov process will be defined as follows:

The states defined in Table 1 lead to a nine-state Markov chain with an absorbing barrier (State 8) and the resulting one-step transition probability matrix is

$$\mathbf{P}_{8\times 8} = (P_{ij}), \text{ where } i = 0, 1, 2, 3, \ldots, 8 \text{ and } j = 0, 1, 2, 3, \ldots, 8. \quad (1)$$

We specify the time interval unit for the probability transition matrix for utilization to be one day, a 24-hour period, since too much information would be lost using a larger time unit such as a week, a month or longer.

Consider the finite number of possible transitions for individuals in the model. Denote by the element

$$P_{00} = \Pr[X_n = 0 | X_{n-1} = 0], \text{ for any } n. \tag{2}$$

the probability that an individual starting in m_0 stayed in m_0 after one time period. Similarly, the probabilities for staying in the same state after one transition are the transition probabilities:

$$P_{00}, P_{11}, P_{22}, P_{33}, P_{44}, P_{55}, P_{66}, P_{77}, P_{88}.$$

Let

$$f_{ii}^n = \Pr[X_n = i, X_v \neq i, v = 1, 2, \ldots, n-1 | X_0 = i]. \tag{3}$$

be the probability that, starting from state i, the first return to state i occurs at the nth transition [13]. There are 81 possible transitions for an individual in this model. State m_8 (termination from the plan) is an absorbing barrier or state, defined by Ross [19] as a state that once entered cannot be exited. This means that the probabilities of transition from m_8 to states m_0 through m_7 are zero and the probability of starting in state eight and staying in state eight is one. Hence in the probability transition matrix (1),

$$P_{80} = P_{81} = P_{82} = P_{83} = P_{84} = P_{85} = P_{86} = P_{87} = 0 \,\&\, P_{88} = 1.$$

The matrix can be partitioned into 4 subsets. The set of transition probabilities, $\{P_{88}\}$, has the following two properties: (1) it has a period of one and (2) since $f_{88}^n = 1$, it is positive recurrent. Combining the previous two properties (1 & 2) leads to the conclusion that $\{P_{88}\}$ is an ergodic set. This set will be represented by the submatrix, $\mathbf{E}_{1\times 1}$ and defined as follows: $\mathbf{E}_{1\times 1} = \{P_{88}\}$. The next submatrix of the partitioned matrix to be considered is the vector of zeroes,

$$\mathbf{0}_{1\times 8} = \{P_{8i} | i = 0, 1, 2, 3, 4, 5, 6, 7\}.$$

Once in the absorbing state the individual cannot leave the state; hence all the cell entries are zero. The third partitioned submatrix to be defined will be the transient states,

$$\mathbf{M}_{8\times 8} = \{P_{ij} | i = 0, 1, 2, 3, 4, 5, 6, 7 \& j = 0, 1, 2, 3, 4, 5, 6, 7\}.$$

The submatrix M includes all the transient states of the Markov chain. The probability of the first return, equation (3), for these states (m_0, m_1, m_2, m_3, m_4, m_5, m_6, and m_7) is less than one. The final submatrix to consider is the transition from a transient state to the absorbing state. This will be defined as

$$\mathbf{L}_{8\times 1} = \{P_{ij} | i = 0, 1, 2, 3, 4, 5, 6, 7\}.$$

An alternative form of the probability transition matrix can now be illustrated with dimensions of partitioned matrices: $\mathbf{E}_{1\times 1}$, $\mathbf{O}_{1\times 8}$, $\mathbf{L}_{8\times 1}$, $\mathbf{M}_{8\times 8}$. It should be noted that the matrix $\mathbf{E}_{1\times 1}$ is equivalent to the identity matrix, $\mathbf{I}_{1\times 1}$. Replacing $\mathbf{E}_{1\times 1}$ with $\mathbf{I}_{1\times 1}$ in the matrix results in the following

$$\mathbf{P} = \begin{pmatrix} \mathbf{I}_{1\times 1} & \mathbf{O}_{1\times 8} \\ \mathbf{L}_{8\times 1} & \mathbf{M}_{8\times 8} \end{pmatrix}. \tag{4}$$

5. Mean Time in a Resident State. Determining the mean time or number cycles an individual occupies in a resident state requires some knowledge of linear algebra and the development of the fundamental matrix for Markov chain with an absorbing state. Kemeny and Snell [14] developed methodology for finding the mean time in each resident state before transition into the absorbing state. They proposed the following. Let $\mathbf{B}^m_{n\times n}$ be a square matrix raised to the power m. If $B^m \to 0$ as $m \to \infty$, then $(\mathbf{I}-\mathbf{B})$ has an inverse, and

$$(\mathbf{I}-\mathbf{B})^{-1} = \mathbf{I} + \mathbf{B} + \mathbf{B}^2 + \mathbf{B}^3 + \cdots = \sum_{i=0}^{\infty} \mathbf{B}^i. \tag{5}$$

For any Markov chain with an ergodic set, let the matrix $\mathbf{M}$ correspond to the set of transient states, as in (4). Then $(\mathbf{I}-\mathbf{M})$ has an inverse, and

$$(\mathbf{I}-\mathbf{M})^{-1} = \mathbf{I} + \mathbf{M} + \mathbf{M}^2 + \mathbf{M}^3 + \cdots = \sum_{i=0}^{\infty} \mathbf{M}^i. \tag{6}$$

Substituting the matrix $\mathbf{M}$ from (4) into equation (5) proves (6). Let

$$\mathbf{N} = (\mathbf{I}-\mathbf{M})^{-1} \tag{7}$$

be the fundamental matrix for a Markov chain with an ergodic state [14]. The next consideration is the number of times for an individual that a transient state is occupied. Define η_{lj} to be the function assigning the total number of times that the process is in state m_j after starting from state m_l (restricting the choices to transient states, $\{m_j | j = 0,1,2,3,4,5,6,7\}$). This quantity will be will be expressed as the sum of indicator variables μ^k_{lj}. After starting in state m_l, let

$$\mu^k_{lj} = \begin{cases} 1 & \text{if the process is in state } m_j \text{ after } k \text{ steps} \\ 0 & \text{Otherwise.} \end{cases} \tag{8}$$

Determining the expectation of the number of cycles an individual stays in a resident transition state, conditional on having just entered the system, follows [14]. The mean number of days spent in m_j after starting in state m_l is $\mathbf{N}_{8\times 8} = E[\eta_{lj}]$, as can be seen from the following argument. It should be observed that $\eta_{lj} = \sum_{k=0}^{\infty} \mu^k_{lj}$. Hence $E[\boldsymbol{\eta}_{lj}] = E[\sum_{k=0}^{\infty} \mu^k_{lj}]_{8\times 8}$. Note that the μ^k_{lj} is the l,j element of $\mathbf{M}^k$. Here $\boldsymbol{\eta}$ is the matrix whose l,j element is η_{lj}. Then

$$E[\boldsymbol{\eta}] = \sum_{k=0}^{\infty} E[\mu^k_{lj}] = \sum_{k=0}^{\infty} \mathbf{M}^k = \mathbf{N}.$$

Denote the expected numbers of days in eight transient states by $\mathbf{T}'$, taken from the proper row of $\mathbf{N}$.

6. Cost. The notation for the cost function is equation (9). Define the fixed cost to be a column vector, where each element of this 9×1 matrix is the averaged costs per utilization state of the system. It should be noted that the elements for the states "no use of services" and "termination from the plan" have no allowable costs associated with them. The cost function can be represented as

$$\mathbf{C}'_{9\times 1} = \{0, c_1, c_2, c_3, c_4, c_5, c_6, c_7, 0\}. \tag{9}$$

The model is defined by multiplying $\mathbf{T}'$ and (9) with the result

$$F(x_i) = \mathbf{T}'_{9\times 1}(x_i)\mathbf{C}_{1\times 9},$$

where x_i is the conditions of interest (gender, age, and diagnosis). The value of the function F is the predicted cost for an individual over a two-year period of January 1, 1996 through December 31, 1997. The vector of utilization, $\mathbf{T}'$, has a dimension of 1×9. The vector of cost, $\mathbf{C}$, has a dimension of 9×1. Taking their product generates a scalar value, $\mathbf{F}_{1\times 1}$, which is the predicted cost given gender, age, and diagnosis.

7. Application - Data. Administrative databases are commonly used for economic evaluation [22]. The claims data used in the model will originate from the OneCare claims database maintained for research purposes by the Health Services and Technology Assessment Program at the University of Texas-Houston School of Public Health. OneCare is an independent physicians association in the state of Texas. The claims covered the period January 1, 1996 through December 31, 1997. The model under consideration requires the claim records and demographic identifiers for the enrollees of the managed care plan. Unfortunately, the database has a few restrictions. The demographic identifiers of marital status, and Socioeconomic Status (SES) are not available. The claims for pharmaceutical services, medical equipment and long term care (skilled nursing facilities) are not collected. With respect to these limitations, the information abstracted for predicting the costs and utilization was age; gender; and respective claim records.

The Physician's Current Procedural Terminology (CPT 97) manual was used in conjunction with the ICD-9 codes to define the states necessary for the model based upon the procedures and diagnostic tests to be included in the table of costs incurred. Validation of the model was addressed. The data were divided into subsets generating two samples, randomly, from the data. From these samples the demographic identifiers gender and age, were determined. Each combination of the identifiers generated a subset of the sample for each disease. The total number of models to be checked was nine. A Chi-Square Statistic, "goodness-of-fit" measure, was used to determine reliability of the predictions based on the model, namely the mean time in each state of the process.

For the purposes of estimation and independent model validation the population was separated into two separate random samples (group 0 and 1). The transition probability matrix for utilization is based on empirical estimation from the data. The actual utilization of the enrollees is used to generate the probabilities of the different states of utilization.

Defining age and gender subgroups is the next step. Due to the size limitations of the data, there are only two age groups, those people less than or equal to 66

Table 2. The attendant allowable costs for enrollees in the OneCare plan

Resident Transient States for the Model	Average Allowable Costs Per Event
No use of services	$0.00
PCP Visit	$61.75
Specialist visit	$82.70
Inpatient (hospital stay per day)	$1,749.43
Emergency Room (ER)	$225.29
Outpatient Surgery	$559.83
Radiology & Outpatient Treatment	$93.17
Pathology	$29.28

years of age and those greater than 66 years of age. The median age is 66 for the population subgroups and was a suitable cutoff point. A second reason for the choice of age cutoff is that an administrator would be interested in knowing the differences between a most likely working subgroup (those less than or equal to 66) and their counterparts that are probably retired. The sample size of the hypertension group was n = 1019. They were split evenly between two groups.

The second part of this model considers a deterministic or fixed cost component. Finding the mean cost in each resident state of cost derived the costs. The attendant costs or charges were derived from applying a table of costs or charges for each episode of disease or event, such as a visit to a physician, emergency room visit, hospital stay, and outpatient surgery or outpatient treatment. The cost will be set for each resident state in the Markov chain. This is realistic in that this is how bills and utilization are usually derived in the health care environment. The focus of this study does not require the cost to be stochastic or random.

The values of cost for each state in Table 2 were computed from the claim records. Each event that occurred during the two-year period was classified as one of the seven states that incur a cost. The values in the table are the averages for the population.

This section will show the results of testing the cost model for the index conditions or chosen subgroups. The analysis of the subgroups will be illustrated in Table 3. The estimated cost for each subgroup is located in Table 4. The chosen subgroups used to predict cost based on utilization were hypertension all categories; age specific; gender specific; gender and age specific. Some adjustments were made due the output of the probability transition matrix. Equation (6) requires a square matrix of transient states. For hypertension the resident state of utilization of outpatient surgery had no occurrences and could not generate an expected mean time. Also, the states of ER and specialist each had a probability of one, thus becoming ergodic and needing to be omitted from the matrix that generated the mean time before absorption. The observed times from the second sample were still used, but the expected time was coded as zero. This was included with the long- range view of being conservative in the estimates.

The sequence of models for the hypertension subgroups was run. The components of the model used that contributed to allowable cost were the utilization states,

Table 3. The results of modeling the subgroups of Hypertension.

Subgroups	Statistic χ^2	Model Fit
Hypertension – group as a whole	3.54	OK
Hypertension & Age 66 or less	2.96	OK
Hypertension & Age greater than 66	3.70	OK
Hypertension & Female	4.11	OK
Hypertension & Female & Age 66 or less	3.23	OK
Hypertension & Female & Age greater than 66	4.76	OK
Hypertension & Male	3.09	OK
Hypertension & Male & Age 66 or less	Unstable	Unable to Fit
Hypertension & Male & Age greater than 66	2.91	OK

Table 4. The predicted costs based on the model are as follows for a two-year period for Hypertension

Hypertension	$3,996.25
Hypertension & Age 66 and under	$3,763.23
Hypertension & Age older than 66	$4,168.60
Hypertension & Female	$3,767.21
Hypertension & Female & 66 and under	$3,516.27
Hypertension & Female & Age older than 66	$3,918.91
Hypertension & Male	$4,250.79
Hypertension & Male & Age 66 and under	Unable to Fit the Model
Hypertension & Male & Age older than 66	$4,505.74

$\{m_1, m_2, m_3, m_4, m_5, m_6, m_7\}$. The critical value changed to the value 11.07 with five degrees of freedom and using the one-sided test with $\alpha = 0.05$, due to loss of one degree of freedom. The results for the hypertension subgroups are in Table 4. The fit of the model for the subgroups was determined to be good for all except one. The subgroup needing scrutiny has the identifiers- hypertension and male & age less than or equal to 66 years old. The utilization states of outpatient surgery and pathology have probabilities equal to one and that left only three states that were transient. This subgroup could not generate a stable transition matrix with just three transient states and low cell counts.

Combining the Markov process and the cost schedule from Table 2 gave estimates for each of the subgroups for the two-year period of January 1, 1996 through December 31, 1997.

The values in Table 4 reflect the results from the full model developed in this study. The trend of the older age group having higher expected costs continues. It should be noted that the costs for the male subgroups are higher than for their female counterparts. The costs in Table 4 are based on the general utilization plan and the schedule of costs for each subgroup. This could be expanded to any subgroup the reader wanted to provide some inference about provided the necessary information is contained in the database the model is being used to test.

8. Summary and Discussion. The aim of this study was to explore a flexible stochastic model to predict costs based upon selection criteria such as diagnosis, gender, and age. The model was tested on a large administrative database of claims. Considering the results, it seems realistic that the model can incorporate any number of conditions and produce an estimate of utilization to be used in the model. There is a restriction. If the number of transitions is small in one or more resident states with the addition of one or more resident states becoming ergodic, then an unstable probability transition matrix is generated. The unstable matrix cannot provide appropriate estimates. The model seems to be able to predict the utilization patterns in the various subgroups. Sample size, alone, does not seem to dramatically affect the "goodness of fit" of the model. The difficulty occurs when the number of transitions is less than ten. Overall, the subgroups that generated stable probability transition matrices provided good estimates of the utilization patterns of the data. There were several limitations to this study that should be addressed in future research. The first limitation was the restrictions due to the database with the lack of demographic identifiers. The absence of ethnicity, marital status, and SES leads to questions about the changes in utilization patterns for these groups of enrollees. A second limitation of the study was the choice of deleting the multiple events per day for an individual. This could have accounted for the states remaining transient in the probability transition matrices. This scenario occurred when the sample sizes were small, less than 200, and the patterns of utilization were minimal, that is when the number of transitions is less than 10. This minimal utilization is more than likely a product of the small sample size. One of the subgroups (hypertension males age less than or equal to 66) had this occur leading to an unstable probability transition matrix and an inability to predict cost for the subgroup The direction of future research for this healthcare problem requires addressing the limitations and changing the some the decisions for inclusion into the model. One possible extension of this study is not to restrict of the number of events on the same day to the first one taken. This would require a much larger utilization array to encompass all the possible pathways per day A third extension allows the cost to be a random function. The model would then contain two random processes and has the potential to be used globally, without the requirement of the cost function to be conditioned depending on the region, nationality, etc. In allowing the cost to be random function, it could be applied to any region without any loss of generality. The analysis that would be required would necessitate the use of two random processes, preferably stochastic. Then the mean and variance could be computed using stochastic integrals.

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