Critical Review of Stochastic Simulation Literature and Applications

for Health Actuaries

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September, 2007

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Funding for this project provided by
the Society of Actuaries' Health Section Council

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I. Introduction

The literature on stochastic modeling within the health area is broad, covering topics from simulating hospital staffing needs, physician behavior, medical technology assessment and health insurance policy. In order to be both feasible and useful, a review of this literature must be limited in the number of topics and type of models included. This is a review of two topics: insurance benefit design and primary preventive services. Articles were selected for review if they described the development of a stochastic model in detail or if they were a companion article describing a model application.

Actuaries use models regularly in their daily work, so they are very familiar with the process of converting real life phenomena into simplified and abstract mathematical models. Our goals in preparing this review were to expose actuaries to the types of stochastic modeling research published in peer reviewed health journals, to suggest ways that actuaries could make use of the modeling techniques or the findings from model applications and to increase actuaries' understanding of policy analysis techniques used by health services researchers. On the advice of the Project Oversight Group, we also prepared a summary of stochastic simulation resources.

Actuaries are experts at developing models to estimate financial outcomes and typically use cell-based deterministic models in their work. By contrast, most of the models reviewed in this report are microsimulations. As described below in Section IV, Review of Simulation Terminology and Methods, cell-based models can be thought of as a middle ground between microsimulation models (where the unit being modeled is an individual) and systems dynamic models (where the unit being modeled is the system itself). Cell-based models group individuals into like cells, perhaps by age, sex and broad classes of health status. A basic assumption is that individuals within the cell are homogenous. Because the unit of analysis in microsimulation models is the individual, in contrast to a cell of grouped individuals, microsimulations have no constraint or assumption about homogeneity of individuals within a cell. However, microsimulation modeling is data intensive and may require techniques and software that are not readily available to a health actuary. In practice, actuaries will need to balance the advantages of microsimulation modeling and the resources required with the financial question to be addressed. If the financial question is one for the short term, traditional cell-based methods may be sufficient. But if the financial question is a longer-term strategic issue, and there is a strong need to understand interacting and dynamic risks, stochastic microsimulation may be a preferred method.

Our review is a glimpse into the vast literature of stochastic simulation. The interested reader is encouraged to seek out additional references, perhaps beginning with the bibliography from this review. If an interested reader experiences difficulty in obtaining a particular article, we recommend he or she contact the corresponding author for assistance.

How the Report is Organized

This report is organized as follows: Section II is a discussion of why the report is relevant to practicing health actuaries; Section III follows with a brief overview of where stochastic simulation techniques have been applied. Section IV is a review of simulation terms and methods; it prepares the reader for later discussion. Section V is a summary of stochastic simulation references that could be used by readers who want a deeper understanding of modeling techniques and applications. Section VI provides the protocol used to select articles for the review. An overview of each article reviewed is found in Section VII; the reviews themselves are included as an appendix. Section VIII describes two applications of stochastic modeling that practicing actuaries should find familiar. The report ends with a discussion in Section IX.

II. Why Stochastic Simulation Literature is Relevant to Practicing Actuaries

Stochastic models are those that include one or more stochastic (random) variables. Monte Carlo methods are typically used to "draw" a value for the stochastic variable from a pre-specified distribution. In contrast, deterministic models assign a value to a variable and that value does not change during the modeling run.

Health actuaries use modeling techniques regularly in their daily work. They are likely to use deterministic models and represent uncertainty through the development and display of a number of scenarios chosen to represent typical assumptions on one hand, and extreme assumptions on the other. These techniques have served health actuaries well and continue to be appropriate for applications that have short projection times and demand a fast turnaround time for the analysis. They are also appropriate where little variation in parameter values or independent variables/parameters exists.

Health actuaries may find that the current environment has changed in several ways that encourage stochastic modeling. First, business demands now include challenging projects such as estimating the financial outcome from medical management programs and estimating selection effects when dissimilar benefits, such as traditional and new consumer directed health plans, are offered side-by-side. Here, both the long-term outlook, and the value gained from simultaneously evaluating or manipulating multiple model parameters which may interact with one another, will frequently favor stochastic modeling. Second, a broad array of data required for modeling are increasingly available from client databases, public databases or published literature. Third, the widespread availability and affordability of high-speed computers with virtually unlimited memory and storage capacity has increased the ease of implementing stochastic modeling. Fourth, stochastic modeling software is more accessible and affordable, and typically implements high quality graphics display capabilities, facilitating the presentation of complex modeling results to lay audiences and clients. In addition, employers, health plans and government payers are struggling to control health care costs. Actuaries can play a significant role in strategic management decisions if they can provide thorough analysis that describes uncertainty in ways that display a range of plausible outcomes, which allows clients to more easily visualize whether a given strategy results in acceptable outcomes.

Later in this report, we describe two practical applications that actuaries may currently face: financial analysis of an obesity management program and small group renewal pricing. In addition to the practical applications, this review of simulation literature offers an exposure to the types of problems being addressed by health care policy analysts and the types of models that are being used to analyze the problems.

Actuaries often evaluate risk and financial viability for the short run, e.g., next year's premium rates. For such a task, a simple deterministic model is fairly easy to develop and often meets the actuary's needs. The additional value a stochastic simulation yields may not be commensurate with the development effort required for some actuarial projects. However, when a more strategic analysis is required, stochastic simulation modeling offers additional value because it can incorporate random variation, interdependencies and feedback loops and produce distributions of plausible outcomes which enhance both the actuary's and client's understanding of the underlying issues.

Ian Duncan, FSA, has 30 years of experience in health care and insurance product design, management, financing, pricing and delivery for life, health and disability insurers and reinsurers. His years of experience provide him with a realistic basis on which to evaluate actuarial techniques. His personal appraisal for the use of stochastic simulation modeling follows:

Stochastic Simulation and Actuaries

Actuaries are major modelers of the future— indeed, actuarial science is all about the uncertainty of future events— so stochastic simulation models would seem to be a "natural" for actuaries. Why is it, though, that this area has received relatively little attention in the past?

To answer this question, we need to understand what we mean by stochastic simulation models and how they differ from other models that we use regularly. Typically, actuaries use deterministic models in the course of their work— that is, models that explore the interactions of multiple variables. The value of such models, in my experience, isn't necessarily the projections that result from allowing models to interact over time, but rather their very determinism. By this, I mean that in order to make a projection for the future based on variables, the actuary needs to have explicitly identified the relevant variables and quantified their impact. In turn, this often requires explicit analysis of historic data to identify relationships, determine independent variables, hypothesize the "shape" of the distribution of outcomes and quantify the relationships. All of this is often a large project, and keeps many actuarial students (and actuaries) usefully employed. Of course, this type of work could be (and often is) performed by a numerate MBA or other analyst.

What differentiates actuarial models? One answer is uncertainty. Modeling uncertain outcomes is what sets actuaries apart. We are trained in risk, the financial counterpart of uncertainty. Risk assessment, risk pricing and risk management—all of these actuarial activities require the application of actuarial training to the modeling function.

However, how to include uncertainty in the model? In our traditional modeling work, we have often picked combinations of variables—perhaps extreme points of the reasonable range, or perhaps a high or low combination scenario—and modeled those. This approach is useful in setting boundaries around the likely outcomes from the model, but doesn't necessarily tell you anything about the distribution of outcomes between the extremes. To determine the distribution in the reasonable range of outcomes requires replication of the model under multiple different scenarios.

A Real-Life Example

I will illustrate stochastic simulation modeling with a real-life case example. My consulting practice is in the area of disease management (chronic care management) finances. Clients retain us to help them price their products, estimate the financial impact of a program and perform outcomes measurement. One aspect of the pricing of chronic management programs is so-called "guarantees" or the amount of its fees that a vendor is willing to put at risk for achieving a particular outcome. The pricing of the underlying services and the expected savings to be achieved from a program are often a deterministic calculation. However, because the savings outcomes are subject to considerable uncertainty, vendors sometimes seek to reinsure the risk of achieving the contracted outcome (savings level). In the event that the vendor does not achieve a particular level of savings, a reinsurer agrees to pay a portion of the shortfall between the guaranteed level of savings and the actual savings. The question that both reinsurers and customers need to answer is: what is a fair net premium (or expected loss level) that the reinsurer needs to charge to accept the risk?

Early versions of our pricing model resulted in a relatively simple, deterministic approach to pricing. We developed two distributions of likely financial savings outcomes, either a normal distribution or a skewed distribution (lognormal). Depending on the expected value of the savings distribution, the target (guaranteed) savings, and the shape of the distribution, it is possible simply to estimate the likely losses.

As we developed the model further, we took a stochastic approach. A distribution was developed for each independent variable in the model (number of members with specific conditions; ability to reach and enroll members; hospitalization rates; behavior change probability, etc.). Different distribution functions were used for different variables, including normal and Beta-functions. The ultimate model was then developed to perform simulations using a Monte-Carlo approach. Values for each variable are assigned by a random number generator, and the final outcome is then dependent on the randomly-generated variables. The simulation is run multiple times, and the result is a distribution of likely savings outcomes that is dependent on the distribution of underlying variables, rather than a specific analytical distribution function, or a few specific scenarios.

The deterministic version of the model was a simpler view, assuming a specific composite distribution of overall results. The stochastic version allows each variable to be selected independently, and contribute to the overall result. Ultimately, we have more confidence in the stochastic-based model because it is based on a strategy of randomly sampling from the population of potential model solutions. Most deterministic models are run such that they generate solutions based on only one iteration, or possibly a few iterations if sensitivity testing or "what if" analyses are performed. With stochastic modeling, each model iteration can be said to result in one "sample" solution, drawn randomly from the underlying distribution of possible solutions (given model assumptions). Thus, a large random sample of model solutions is to be preferred to a solution from a single iteration solution—which is analogous to a sample of one. Once an adequate "sample size" of iterations has been achieved, there is little gain to precision or validity from further iterations.

Other Applications

There are clearly new, emerging areas of actuarial practice that stochastic simulation fits very well. Enterprise Risk Management (ERM) is one: what are the important drivers of risk in a health insurance enterprise? We can list some potential variables:

- *Members and their risk profiles.*
- *Member choices, anti-selection and termination patterns.*
- *Employer groups, options available to them, benefit choices, employer termination rates.*
- *The company's competitive situation, number of competitors and stage of the underwriting cycle.*
- *Sales volumes and quality of new business.*
- *Outside regulatory climate.*
- *Provider groups, network quality, provider compensation and contracts.*
- *Administrative processes, costs, staffing and efficiency.*
- *Capital requirements and capital structure.*
- *Investment environment and investment income.*
- *Exogenous variables, such as the general inflation level, the medical inflation level (and the related resource demands and shortages that cause medical inflation).*
- *Exogenous threats such as influenza epidemics, natural disasters, and man-made disasters.*

Each of these areas deserves considerable thought and would be a candidate for a full model, with its own independent variables driving the results, which would then feed into the summary Enterprise Risk Model.

Several things need to be taken into account, however, if one is concerned about enterprise risk. One area is endogeneity, where variables that you thought were independent (and modeled as such) turn out not to be so. For example, the administrative processes that a company employs, especially its claims payment processes, depend on its free cash and capital. A slow-down in the payment of claims, however, in turn will affect the provider contracts and the quality of the provider network. A negative impact on the provider network will affect the member and employer attrition rates as well as the new sales volumes, which in turn will affect free cash flow.

A model that projects these variables without the interactions (or a feed-back mechanism) is likely to miss the full effect of a sudden shift in one of the variables.

The typical reaction to a modeling problem such as this one would be to build a one-dimensional model—for example, what is the effect on trend of changes in provider reimbursement? But a few moments' thought, keeping in mind the list of variable interactions, will show that a single-dimensional model is unlikely to capture all the impacts of a single change. Nor will such a model account for the likely feed-back that will ultimately result as the effect of a change ripples through all the inter-related areas on the company.

A complete model of the corporation that will enable the actuary to assess enterprise risk must allow not just for stochastic events (unexpected shocks, or the random assignment of certain parameter values from a known distribution, for example) but also the interdependency of key variables. Clearly, a sophisticated model is required if one wishes to address adequately the potential range of outcomes and their effect on the company's solvency and capital.

A Word of Caution

I began my career not as an actuary but as an economist, in the 1970s. At the time, with computers just beginning to show their power, I was fascinated by models of the economy. For a while I even studied (I shudder now at the thought) Soviet Union central economic planning, as a model of what a group of smart people armed with a computer could do to relieve all the ills of capitalism. The centrally-planned model of the economy is now rightly dismissed as a futile dream. It is hardly possible to understand, let alone model or control the interactions of individuals in their economic life. I mention this as a caution, because models, however good they may be, cannot be a substitute for the real economic and risk-taking relationships that are the value of the health insurance company. But the discipline of identifying and quantifying the key variables and their inter-relationships will always be a valuable task for actuaries, and will help the understanding of the insurance enterprise.

In Conclusion

In conclusion, this is an exciting new area for actuaries, and holds great promise. It is an opportunity for the health actuary to add value, not just to their employer but to their career as well.

III. Subject Areas Where Simulation Has Been Applied

Stochastic simulation techniques are often used for policy analysis. In particular, simulation has been used to study public insurance expansion, health delivery resources, insurance benefit design and primary prevention services. Health economists, health services researchers and statisticians frequently use stochastic modeling techniques to address health policy and strategic issues.

Actuaries also use stochastic simulation techniques, but have generally focused on investment returns and risk analysis of long-term contracts: life insurance, annuities, disability insurance and long-term care.[1, 2] However, a recent call for proposals for modeling mortality and lapse risks in life insurance shows an expanded interest in stochastic modeling.[3] In addition, the Society sponsored a modeling session at the 2005 Spring Meeting: Stochastic Modeling in Health Insurance. The applications covered at the session were IBNR valuation, strategic asset allocation policy for health insurance assets and medical claim costs.[4]

The two topic areas in this our review, insurance benefit design and preventive services, are areas of interest to practicing health actuaries. Exposing the health actuary to applications of stochastic modeling techniques in these areas gives the health actuary insight into the techniques used by other professionals operating in the health field. Other health-related topics are also reasonable areas for developing stochastic models and the interested actuary could easily adapt the literature search methodology used here to discover applications in other areas.

Regardless of the topic area, stochastic modeling enlightens the actuary on the underlying volatility of the phenomenon of interest. Understanding volatility and anticipating variation is the actuary's bread and butter: the actuary's job is to evaluate risk generated by uncertainty—risk associated with a stochastic phenomenon.

IV. Review of Simulation Terminology and Methods

This section defines many of the terms and types of models that are described later in the report. In the following paragraphs, key terms are italicized, with some terms being used in the context of describing other key terms. While we have attempted to apply a logical ordering of these terms, the reader should be aware that in some cases, terms are used that are not defined until later in the text.

Decision analytic models have recently been characterized as "an explicit way to synthesise [sic] evidence currently available on the outcomes and costs of alternative (mutually exclusive) health care interventions."[5] In the context of the articles reviewed for this report, simulation modeling can be seen as one type of decision analytic modeling strategy.

A *static model* is defined by the characteristic that the model equations are solved in a single pass. While static models may be used in simulations, in comparison to *dynamic models*, they lack valuable features such as providing a way for a system to evolve over time, taking into account the timing and sequencing of events relative to one another, and accounting for variability in a system over time. Spreadsheet models are one well-known example of this type of model. Largely because of the added value, one of the defining characteristics of *most* simulation models is that they are *dynamic*. In dynamic models, systems of equations are solved iteratively, allowing the behavior of a system and its outcomes to evolve over time. Such models allow for time based variance, as well as interaction of parameters within the model across time, providing, among other things for opportunities to observe the impacts of the timing and sequencing of transitions. While simulation can be as straightforward as static, deterministic modeling with scenario testing, stochastic simulation is defined by the inclusion of at least one random variable. It is primarily in the context of dynamic models that the introduction of random or stochastic components becomes useful.

Deterministic vs. *stochastic* models. That our review includes only one example of a deterministic model[6] highlights the fact that the majority of simulation modeling is conducted in the stochastic framework, the typical hallmark of which is the inclusion of one or more stochastic (random) variables. By contrast, in a deterministic model, variables and model parameters are not subject to random fluctuations, meaning the system is entirely determined by the initial conditions chosen. The inclusion of stochastic elements in simulation models is typically accomplished through the use of *Monte Carlo* methods in which variable or parameter values are drawn at random for each iteration from a pre-specified distribution, whose properties are known and typically specified as part of the model setup. The essential principle behind the Monte Carlo method is that one can observe the behavior of a statistic in a random sample empirically by drawing a large number of random sample values from a known statistical distribution and observing the behavior.[7] Thus, in Monte Carlo based simulations, one or more variable or parameter values in the model are set probabilistically, based on known distributions (e.g., values may be drawn from a normal distribution such as N(0,1)) that presumably approximate the real-world value distributions observed for the phenomenon of interest. Health actuaries frequently use a claims distribution as the underlying distribution when using Monte Carlo techniques.

Agent is a term used to describe the individuals or entities that populate or inhabit a target system that is being simulated. Agents are the most basic units or building blocks of a simulation. In some models, such as *system dynamics* models, the model may contain only a single agent (e.g., a health insurance plan). By contrast, in microsimulation models, there are typically many agents that are characterized more or less complexly depending upon the sophistication of the model. In these models, all agents are assumed to operate at the same "level" in the model (e.g., agents may be specified to operate at the individual level, or at the level of the population or universe). In a simulation of a health promotion program, the agents might be the individual members of a health plan or employees of a firm. The dynamics of these multiple agents, however, do not extend to the agents communicating with or influencing one another. Such further levels of "realism" are found in other classes of simulation modeling including multi-level simulation, cellular automata and multi-agent models[8] but none of these model types were seen in the topic areas reviewed for this report.

A *Markov model* describes a sequence (or "chain") of probabilities of transitions occurring between a defined set of "states" over time where the probability of an event occurring is a function of a preceding event having occurred. In the context of a simulation, the key characteristics of the Markov model are the presence of a random element applied to draw samples from a probability density function to derive parameter values in the model. This element is typically one or more stochastic transition probabilities that are assumed to depend on the immediately prior state or set of states in the model, but not earlier states. Thus, without some further elaboration (as discussed below), such models are "memory-less." In addition, Markov models are most frequently employed using distinct and mutually exclusive sets of states. The "memory-less" character of Markov models limits their ability to represent reality, particularly in situations where the phenomena of interest are clearly affected by past historical states. In one of the papers reviewed here (Core diabetes model[9]) a Markov model simulation was elaborated to have a form of memory through the use of "tracker" variables used to carry forward information from past model states that were allowed to affect current transition probabilities in the model. Such functionality has recently become available in "off-the-shelf" simulation software (for example TreeAge, *www.TreeAge.com*).

Markov models are classified by whether the time process involved is continuous or discrete, and whether the states of the model are continuous or discrete. Most commonly employed are Markov models with *discrete time* and *discrete states*. In discrete time Markov models, the system of states and transitions proceeds in a series of discrete, equidistant time-steps, whereas in a continuous time Markov model, the system proceeds with variable durations of time spent in different states. The majority of simulations that we have reviewed here, and nearly all of the microsimulation models in particular, fall into the broad category of discrete-state (or discrete-event), discrete-time, Markov chain models. However, the Macdonald models [10, 11] were described as continuous time Markov.

Similarly, most of the simulations we reviewed are *dynamic simulation models* rather than *static simulation models* (the Caro et al.[12] article being an example of the latter). With the inclusion of *stochastic* parameters in the model, the evolution of *dynamic models* over time through multiple iterations is not pre-determined. With iterations occurring over typically *discrete time*-steps, often representing a simulated year of experience, dynamic simulations are frequently used to make relatively long-range projections of systems. By contrast, *static simulation models*, which don't evolve over multiple iterations over simulated time, are restricted to shorter-term projections of systems or populations.

System dynamics models represent a conceptually different type of simulation model from microsimulation modeling. Perhaps the most obvious difference between a system dynamics model and a microsimulation is that, while, as the name would suggest, microsimulation models are specified with much detail at the micro level—modeling the transition probabilities and outcomes of multiple *agents* which make up the basis of the macro-level system described by the model—*system dynamics* models are defined only at the macro-level, with the target system itself (e.g., a health insurance plan) being the only "entity" in the model. *System dynamics* models characterize a target system using an interrelated set of *difference equations* or *differential equations* to derive the system "state" at a point in the future, starting from its current state as described by a set of starting parameters.[a] The model described by Tengs, et al.[13, 14] that we have reviewed for this report is the only example of a system dynamics model that we found being applied within the chosen health topics.

Cell based models (Naidoo, et al.[15]) can be thought of as a type of middle-ground between *microsimulation models* and *system dynamics* models. *Cell based models* may start with specification of individuals, elements or *agents* within a larger system or population, but prior to model estimation, these elements are grouped into a matrix of cells, the dimensions of which are based on the aggregation of characteristics of the individual elements. A key assumption here is that all elements within a specific cell are homogeneous. Actuaries typically work with age/sex cell-based models.

Yet another type of simulation model, *multi-state, dynamic life-table* models (of which the PopMod model used by Lauer et al.,[16] and reviewed here is the first published example) are designed to simulate the mortality experience of a simulated population under the force of two disease conditions that are allowed to interact, as well as a "background" force of mortality. This type of model differs from other multi-state life table models in that it does not assume statistical independence between competing causes of death (a typical assumption of competing risks models) and because it models age and time independently.

[a] While both *difference equations* and *differential equations* characterize a system at state t+1 as a function of its state at time t and a vector of parameters describing the system, the key conceptual distinction is that the former indexes time in terms of arbitrary and equidistant units (i.e. *discrete time*), while the latter indexes time based on a specified scale and in infinitesimally short increments (i.e., *continuous time*).

V. Simulation References

While our primary purpose here was a review of simulation literature that described model development and application, in the course of our work we uncovered a number of tutorials on simulation modeling. These tutorial articles give additional background and description for actuaries who are interested in simulation and applications within health care. Current information on simulation may be found at the Web site of the Winter Simulation Conference, www.wintersim.org. From the main Web page, one can access programs, abstracts and full papers from past conferences. Interested readers may want to start with the *Introduction to Modeling and Simulation*[17] from the Proceedings of the 2004 conference. An older paper from the 1999 conference addresses use of simulation in health care—*A tutorial on Simulation in Health Care: Applications and Issues.*[18] Two articles provide overviews of the value of simulation modeling for health care: *An Agenda for Healthcare and Information Simulation and Social Modelling*[19] and *Public Policy: Application of Microsimulation Modelling in Australia.*[20]

A number of articles offer descriptions of modeling techniques and their advantages. A pair of tutorial articles describing model types and applications to population screening give good background: *Statistical models for cancer screening*[21] and *Costs and Effects of Chlamydial Screening: Dynamic versus Static Modeling.*[22] Two articles describe models in the context of economic analysis of medical treatments: *Pharmacoeconomic Analyses Using Discrete Event Simulation*[23] and *Understanding Clinical Trials, Simulation Modeling of Outcomes and Cost Effectiveness.*[24] Three articles provide good background for decision analysis modeling and Bayesian approaches. Although the application they describe is economic evaluation of pharmaceuticals, their descriptions of models approaches are general: *Use of pharmacoeconomics in prescribing research. Part 5: modeling – beyond clinical trials,*[25] *A*

Bayesian Approach to Aid in Formulary Decision Making: Incorporating Institution-Specific Cost-Effectiveness Data with Clinical Trial Results[26] and *Handling Uncertainty in Cost-Effectiveness Models.*[27] Many of these tutorial articles begin with modeling definitions and will be useful to novices.

Two other resources were cited in the previous section, both of which may be useful in their entirety for general reference and overview: *Monte Carlo Simulation*[7] *and Simulation for the Social Scientist.*[8]

VI. Literature Review

This section describes the protocol we used for finding and selecting articles for the review.

Databases

We searched two comprehensive bibliographic databases to identify articles for review—PubMed and EconLit. PubMed is a publicly available resource accessible electronically at www.pubmed.gov. The National Library of Medicine's PubMed service includes over 16 million references dating back to the 1950s and covers the fields of medicine, nursing, dentistry, veterinary medicine, the health care system and preclinical sciences. EconLit, the fundamental research tool in economics, is the American Economic Association's electronic database that indexes more than 30 years of international literature on economics. EconLit is available at licensed libraries and on university Web sites.

Selection of Articles for Review

We began our literature search by casting a wide net for abstracts of articles that met our criteria, using both Pubmed and EconLit. For each separate database searched, Table 1 displays the exact search terms used, the sequence in which terms were added, the Boolean logic (e.g., "or," "and," and "not" terms) used to concatenate search terms, and the number of "hits" resulting at each step. We searched for English language articles published during the interval 1985-2005. So, for instance, from the PubMed database, searching for records containing the strings "simulat" in the title, or "computer simulation" as a major heading, we identified an initial 114,263 article abstracts. Adding the list of prevention related terms, enumerated in Table 1 reduced this list to 581 articles. The addition of further search terms ultimately reduced the set of potential prevention related articles from the PubMed database to 315. A similar search PubMed for insurance related articles yielded 208 candidates. A parallel set of searches was conducted in the EconLit database, yielding 23 prevention related articles and 77 insurance related articles.

Thus, we began with 623 abstracts—338 primary prevention articles and 285 insurance benefit design articles. We reviewed each of the abstracts and selected those that met two criteria—the abstracted article described a simulation study and it included a description of the model development. From the abstracts, we selected 57 for full text review (32 primary prevention and 25 insurance benefit design). Of those 57, we selected 25 articles to review for this report, seeking a roughly equal number of articles addressing primary prevention on the one hand, and insurance benefit on the other. All 25 were confirmed to be within our topics of interest, were simulation studies and described model development. The number of articles to include (25), was predetermined by the scope and budget of this project. The list of 25 articles was reviewed with the Project Oversight Group (POG), the Society of Actuaries' committee assembled to oversee this project. Feedback from the POG led to slight revisions of the final articles selected: two articles describing the use of simulation for pricing catastrophic insurance were added and two articles describing simulation of smoking-cessation efforts were deleted. The final list of 25 articles in this review is found in the bibliography.

Table 1. Search Strategies and Results

	Number of Abstracts
Prevention Abstracts from PubMed	
simulat* [ti] OR computer simulation [majr:noexp]	114,263
AND prevention terms (below)	581
AND NOT herd* [ti]	578
AND publication dates 1/1/1985-3/3/2005	544
AND model* [tw]	325
AND English	**315**
Prevention terms: primary prevention [majr:noexp], health promotion [majr:noexp], health behavior [majr:noexp], preventive health services [mh:noexp], "population health," "preventive services," "preventive care," preventive [ti], (immunization [majr:noexp] OR vaccination [majr:noexp]), (smoking cessation [majr:noexp] OR smoking/pc [majr:noexp] OR (smoking [ti] AND cessation [ti])), obesity/pc [majr:noexp], (physical [ti] AND activity [ti]), costs and cost analysis [majr].	
Prevention Abstracts from EconLit	
simulat AND prevent AND (health OR medical)	**23**
Total Prevention Abstracts	**338**
Insurance Abstracts from PubMed	
(computer simulation [majr:noexp] OR simulat [tw]) AND insurance [tw]	238
AND English	211
AND publication dates 1/1/1985-2/8/2005	**208**
Insurance Abstracts from EconLit	
simulat AND insurance AND (health OR medical)	77
Total Insurance abstracts	**285**

Method of Evaluation

For each article, a summary review was prepared. The summary review was designed to answer a number of questions relevant to practicing actuaries:

- What question was being asked?
- What was the model trying to measure?
- What population was modeled?
- What were the events, states, circumstances and interactions to be simulated?
- What was the time frame for the simulation?
- What were the conclusions?

To answer those questions, the summary review form was designed to include the following sections:

- **Article**: Author, Title/Source
- **Context**: Description, Outcome of Interest
- **Model**: Type, Software
- **Model Quality**: Data Sources, Parameters, Simplifying Assumptions, Duration/Time Perspective, Iterations per Scenario, Validation, Sensitivity Analysis
- **Evaluation**: Strengths/Weaknesses, Presentation of Results, Interpretation of Results, Value to Decision Making, Ease of Implementation, Further Reading

All reviews are attached in Appendix A, listed alphabetically by first author.

VII. Results by Substantive Topic

This section gives a brief overview of each article within its topic area. A full review of each article can be found in Appendix A, listed alphabetically by first author.

Insurance Benefit Design—Modeling Health Care Utilization and Costs

Buchanan et al.,[28] Keeler et al.,[29] and Marquis[30] used stochastic modeling to answer questions about selection and utilization under various insurance benefit designs. All three teams based some of their parameters and distributions on data collected during the RAND Health Insurance Experiment (HIE). Although the HIE data are somewhat dated, they provide a rich source from which to develop distributions—and the authors using the HIE data modified it to be current for their work. These three articles were published over 10 years ago, but the techniques they used are still relevant to modeling efforts today. Buchanan et al.[28] and Keeler et al.[29] based their model on demand for episodes of medical care under a full coverage insurance contract; their simulations estimated the impact of varying insurance benefit designs on health expenditures. Marquis[30] also used the HIE data, but focused on adverse selection. All three of these articles offer examples of modeling techniques that continue to be of interest today. Actuaries may consider investigating development of such models and the value those models would have to actuarial clients.

One noteworthy aspect of the Buchanan et al.[28] and Keeler et al.[29] articles is the use of episodes of medical care as the unit of analysis. Actuaries now have the advantage of commercially available episode groupers, which use diagnosis and procedure codes to aggregate data into meaningful treatment episodes. Using client administrative data grouped into episodes of medical care, actuaries could develop distributions of episodes which represent care-seeking by individuals, and perhaps family units. Models developed with episodes as the unit of analysis allow the actuary to test utilization and expenditure within various insurance designs more thoroughly than can be accomplished using population cell-based approaches.

The Yang et al.[31] paper is a good representation of simulation work developed by economists to answer a typical actuarial question: what is the impact of a new benefit plan on short-term and long-term health care expenditures? Yang et al.[31] recognize the interaction between an insurance benefit (Medicare drug coverage) and health outcomes, which in turn impacts non-drug health care spending. Yang et al.[31] present a five-year simulation that captures both short-term and long-term outcomes.

The article by Muldoon and Stoddart[6] describes a deterministic microsimulation to evaluate the impact of a competitive provider system in Ontario, Canada. (This is a deterministic model, yet the approach and topic are useful.) Two types of provider reimbursement were modeled: fee-for-service (FFS) and capitation. Covered members chose FFS or capitated providers and their choice was assumed to be influenced through the average per capita cost, which was experienced by the member as an enrollment charge. Although the article was published in 1989, the type of question being modeled is still very relevant today: to what extent will provider price competition influence consumer purchasing patterns when consumers have a financial stake in the payment of health care? The Muldoon and Stoddart[6] model was focused on provider competition for members, with members feeling a financial impact through a premium or enrollment charge. Today's questions being addressed by both health actuaries and health services researchers are focused in provider competition through cost and quality, with consumers experiencing the financial impact through premium and cost-sharing. The Muldoon and Stoddart[6] deterministic approach may be worth considering to better understand the potential selection and utilization outcomes in the relatively new consumer driven health care market. The modeling effort would be enhanced by using stochastic methods.

Insurance Underwriting

A pair of articles by Macdonald et al.[10, 11] describe the use of stochastic modeling for critical illness insurance underwriting. The authors use incidence data from population studies to estimate the number of insurable events (coronary heart disease event, stroke, cancer, kidney failure and disability). The articles provide detailed description of data sources and development of rates of incidence, but the authors do not adequately describe how they developed a critical insurance premium for their event models.

Macdonald et al.[10, 11] refer to similar models developed within the medical/health management sciences, in particular, they cite Babad et al.,[32] which is also included in this literature review. Macdonald et al.[10, 11] note differences in motivation, model form and range of coronary heart disease (CHD) outcomes modeled. This comparison is illustrated in the following chart.

	Macdonald et al.[10, 11]	**Babad et al.[32]**
Motivation	Quantify insurance risk	Intervention strategies to reduce risk of CHD
Model form	Continuous time Markov	Discrete-time Markov
Range of CHD outcomes	Only outcomes that trigger an insurance claim	Broader range of outcomes included

This comparison suggests that models, similar to these developed particularly for an actuarial audience, are being developed more generally in other disciplines and may be adapted for actuarial purposes.

Economic Analysis of Medical Treatments

We review four articles that describe modeling efforts to compare the costs and outcomes of alternative medical treatments. Two of them (Caro et al.[12] and Kong et al.[33]) use traditional Monte Carlo methods, the other two (Cooper et al.[34] and Cooper et al.[35]) introduce the use of Bayesian Markov Chain Monte Carlo simulation models. The Cooper et al.[34, 35] articles describe themselves as "decision-analytic models," (see definition in Section IV). Decision analytic modeling is usually undertaken with the objective of deciding upon which of two or more mutually exclusive interventions should be preferred, based on assessment of their relative cost-effectiveness. Actuaries with an interest in medical management may want to review this set of articles on cost-effectiveness modeling as an introduction to the types of methods available and the medical technologies to which they can be applied.

Caro et al.[12] and Kong et al.[33] are studies that compare the costs and outcomes of alternative treatments for a given condition. Caro et al.[12] used simulation to estimate direct medical costs for migraine treatment and indirect costs of migraine due to lost time from work and non-work activities. The authors did not, however, compare the costs and outcomes of the new therapies to customary therapies, so the reported results have limited value to a medical manager making coverage decisions or an actuary forecasting future expenditures. While the article might have been a useful example of a microsimulation using Monte Carlo techniques for pharmacoeconomic research, it doesn't supply enough detail to really understand the modeling effort and the model appears to be proprietary.

The Kong et al.[33] study models the financial implications for a hospital when drug-eluting stents were added as a treatment option for patients with coronary heart disease. This review was intended to encompass a fairly broad spectrum of simulations, ranging from low quality to high quality projects, and from the basic to the sophisticated. The Kong et al.[33] paper falls into the latter category on both counts. The main outcome was net profit that resulted from differing reimbursements and costs for drug-eluting vs. bare stents. The authors modeled treatment pattern changes in the number of patients treated with current therapy (bare stents) to drug-eluting stents and the percentage of patients requiring repeat treatment. This was a fairly straightforward simulation, which might have been estimated as well using a deterministic spreadsheet approach.

The two articles by Cooper and various colleagues[34, 35] describe the use of Bayesian Markov Chain Monte Carlo (MCMC) simulation for decision analytic modeling. Both articles begin with a brief description of a frequentist simulation approach. The authors then briefly describe the Bayesian MCMC approach and the advantages it holds over the frequentist approach. The main benefit is the ability to incorporate external information. Both articles illustrate the outcomes of the two approaches; each illustration is a comparison of two potential treatment options for a condition. These two articles may encourage the interested actuary to delve into Bayesian modeling techniques for decision-making models, but in and of themselves they cannot describe the process thoroughly. However, the authors do suggest references for further reading, citing the Web location for WinBUGS modeling software, and including the WinBUGS software code in the articles.

Primary Prevention

Several articles in our review address the health and health care expenditure of primary prevention. Most modeling efforts focus on a particular prevention intervention such as smoking cessation or a disease such as diabetes or heart disease. As health plan administrators, employers and government payers search for methods to contain the growth of health care expenditure through disease management and health behavior initiatives, the financial and health outcomes associated with prevention take on greater importance for actuaries.

Screening

Davies et al.[36] use discrete event microsimulation to estimate the population impact of a one-time Helicobacter pylori infection screening on risk of peptic ulcer, delayed risk of gastric cancer, mortality, and costs. This study used national data from the United Kingdom along with results published in peer-reviewed papers. The model does not appear to be publicly available. The value of this article is as an example of how to construct a model to estimate health and economic impacts of a screening program for a particular condition.

Smoking cessation

We selected four articles that modeled the effects of smoking cessation efforts. Two articles by Tengs et al.[13, 14] are applications of the Tobacco Policy Model developed by Tengs and colleagues with the Health Priorities Research Group at the University of California, Irvine. The main outcomes of the Tengs et al.[13, 14] modeling effort are cost-effectiveness measured in dollars per quality adjusted life year (QALY) and medical costs; the authors estimate the societal impact of various smoking cessation programs. Tengs et al.[13, 14] use a number of publicly available data sources, including the Current Population Survey, the National Health and Nutrition Examination Survey, and the US Census. The Tengs et al.[13, 14] modeling effort was included in this review as an example of a system dynamics model. In addition, this pair of articles represents the type of health behavior analysis that can be accomplished with publicly available data.

In contrast to Tengs et al.[13, 14], a pair of articles by Warner et al.[37, 38] use microsimulation to estimate the impact of smoking cessation programs on medical costs and mortality. Warner et al.[37, 38]. base their modeling effort on data from managed care organizations rather than public data sets. This type of long-term analysis is valuable to actuaries who are advising their clients on long-term strategies and trying to understand the impact of a current program decision on future outcomes. A prime example of that type of work was recently published by Douglas Levy.[39] He investigated the costs and benefits of covering smoking cessation interventions from the insurers' and employers' perspectives.

Coronary Heart Disease

Two articles in the review model the impact of physical activity on coronary heart disease. The Babad et al.[32] model is a microsimulation, while the Naidoo et al.[15] article describes a cell-based aggregate model, a model type frequently used by actuaries. The outcome of the Naidoo et al.[15] model was heart disease mortality and the question to be answered was the impact of physical activity interventions on mortality over a 25 year time period. The Naidoo et al.[15] article was published in 1997 and used a cell-based approach. An interesting value comparison of microsimulation and cell-based modeling, in particular referring to the Naidoo et al.[15]

PREVENT model, is found in *How good is the Prevent model for estimating the health benefits of prevention.*[40]

The Babad et al.[32] model was designed to assess the impacts of various primary prevention strategies on use of health care resources. The model described by Babad et al.[32] was under construction at the time of their publication in 2002, but we did not find further publications emanating from this work. We included the article because it represents a fairly sophisticated application of the microsimulation technique that required more input than could have been produced by a simple application of common sense assumptions. Heart disease is one of the most expensive conditions and a frequent target of disease management, health behavior change and other medical management initiatives. For actuaries interested in modeling of coronary heart disease, a review of 75 CHD policy models, including Naidoo et al.[15] and Babad et al.[32] was recently published by Unal et al.[41] in Bio Med Central public health and is available through their open-access system at *http://www.biomedcentral.com/1471-2458/6/213*.

Diabetes

We reviewed two pairs of articles that report on the development and application of models specific to patients with diabetes. The older articles by Eastman et al.[42, 43] were published in 1997. Part I of the pair described the development of a microsimulation of a population of individuals who were newly diagnosed with non-insulin dependent diabetes (NIDDM). The model projects the individuals through life until death or age 95; the individuals were subject to 14 health states which were complications of NIDDM. Treatment parameters could be modified to estimate the impact of treatment change on health and direct medical costs. Eastman et al. [42, 43] used data from various epidemiological studies and Medicare reimbursement rates. The pair of articles are valuable as examples of how to develop and implement hazard rates and projection of individuals from year to year. It is unclear whether the model is available publicly.

Another pair of articles, from Palmer et al.[9, 44] describe the development and validation of the CORE diabetes model, another microsimulation model of diabetes. This pair of articles provides detailed and clear explanation of microsimulation model development—providing perhaps the most thorough descriptions of both model development and characteristics of all the articles included in this review. The CORE model projects both clinical costs and outcomes for populations using a series of submodels which simulate multiple complications of diabetes. The CORE model was developed for commercial use and is a useful tool for comparing diabetes management strategies.

Depression

Mental health disorders also consume a large share of medical expenditures and are often the focus of disease management programs. The model developed by Patten[45] assessed the efficiency of different treatment strategies to reduce the population prevalence of depression. Patten addresses the question of whether the prevalence of depression is reduced more effectively by increasing antidepressant use overall in a population or by focusing increased long-term treatment on those with recurrent depression. The model suggests that a larger population health impact—and an associated expenditure impact—might be obtained through selected and intensive treatment to reduce depression relapse. Patten provides enough detail in the article to allow actuaries to replicate a similar modeling project for their population.

Population Models

The final articles in this review describe the development and potential uses for population models. Actuaries working with public programs or public policy should find these modeling efforts to be applicable to their concerns. Alternatively, actuaries may adapt the population approach to fit their population of interest, perhaps an employer group or covered members of a health plan. PopMod, described by Lauer et al.,[16] is stated to be available from the WHO (World Health Organization) Web site. It is a dynamic, multi-state life table model designed to simulate the mortality experience of a population under the force of a background mortality rate and two interacting disease conditions. PopMod was designed to be generic and therefore applicable to multiple populations and multiple disease states. Its primary purposes are to describe the evolution of a population's health over time and to model measures of effectiveness for intervention and cost-effectiveness studies.

In the second article, Wolfson[46] describes the motivation for and methods used to develop the Population Health Model (POHEM) microsimulation. At a minimum, the Wolfson article is valuable for its comparison of cell-based modeling to microsimulation. POHEM is a microsimulation of a national population, and at the time the article was published in 1994, the model was still under development by Statistics Canada. The interested reader can find further information on current state and uses of POHEM at the Statistics Canada Web site (*http://www.statcan.ca/english/spsd/Pohem.htm*).

VIII. Practical Application for Health Actuaries

The general modeling strategy used by most of the simulation models reviewed in this report also applies to many work situations for health actuaries. When an actuary is asked to estimate pricing or financial outcomes for a program that impacts specific events within a population, the actuary needs to identify the population of interest, define the events that can happen to individuals in that population, develop contingency tables or distributions that determine the frequency of the events, model the incidence of events in the population over time and measure health care expenditure or other outcomes of interest that develop in the population. Two applications of this general modeling strategy follow: financial analysis of an obesity management program and renewal pricing.

Application: Obesity Management Program

Financial analysis of an obesity management program is of practical interest to health actuaries. Obesity has become a problem of great concern for both public health and financial reasons. Several researchers have identified the additional health care costs associated with overweight and obesity.[47, 48] Because obesity is directly related to high cost chronic conditions such as heart disease and diabetes, payers are interested in programs that can impact obesity and reduce its detrimental impact on health and health care costs. There are risks of ill health and health expenditure due to obesity and there are financial risks of implementing an obesity management program as well as taking no action at all. Similar to programs for chronic disease management, an obesity management program will have early costs of start-up, but the expected savings may not be seen until much later. An actuary pricing an obesity management program could follow the modeling strategy used by several of the authors whose articles are covered in this review, in particular the modeling strategy used by Warner et al.[38] Warner's area of interest was smoking cessation, but the similarities between modeling of smoking cessation and obesity management are many.

To illustrate a simple example, suppose a health plan wants to reduce health care costs by offering an obesity management program, such as Weight Watchers®, to help members lose weight and reduce their body mass index (BMI). The health plan leadership wants to know if it makes good financial sense to offer the program because the benefits of weight loss are not immediate and membership turns over at a rate of 15 to 20 percent per year. Should the health plan invest in a weight loss program for its current members when the benefit of the program may accrue in the future when some of the members in the program could possibly transfer to a competing health plan? Along with membership turnover, there are many unknowns about the obesity management program: How many members will enroll? Will they persist with the program? How much weight will they lose? How will their weight lost impact health care spending and when? The health plan hires an actuary to help answer these and additional questions: Which members should be offered the program? What price should the client pay for the weight loss program? What price, if any, should members be charged for the program? What return should the client expect on the investment? The actuary could make a simple, back of the envelope**.** estimate for the client, or could develop a model that integrates the many variables in question and allows some of them to be random, and thus gives a range of plausible financial outcomes for each scenario of prices and program implementations.

The actuary ultimately decides to develop a stochastic microsimulation model because it would offer the health plan a better description of the long-term impact of the obesity management program by virtue of its relatively long-term timeframe for projection. Although the actuary's usual work has a short one- or two-year time frame, s/he knows that the costs and benefits of an obesity management program are long-term so the tools used to analyze the program also need a long-term perspective. S/he begins model development by identifying the population of interest and describing the population characteristics necessary for the model development. For this project, those characteristics would include age, sex, BMI, health care cost and chronic condition status. A number of model parameters are uncertain and therefore s/he decides to define them as stochastic: percentage of eligible members who enroll in the program, percentage of program enrollees who persist in the program, BMI change for program participants and non-participants, expected health care cost after program initiation as a function of BMI or BMI change. Cost of the obesity management program is well defined and will be entered with both fixed and variable components. S/he runs multiple iterations of the model, making random draws at the start of each iteration to set the stochastic parameters. Monte Carlo techniques will be used to determine the events for each member in each time period: participate in the obesity program or not (assuming eligible), amount of BMI change, health care costs as a function of BMI or BMI change, continued enrollment with the health plan or not. S/he projects 20 years for each iteration, starting with a population with the same characteristics as the current membership of the health plan. At the end of each iteration, s/he computes the present value of health care costs and the cost of the obesity program. S/he compares the average total expenditures that result when the obesity program is in place to the average total expenditures that would result under the status quo. That comparison is what the health plan needs for its decision about whether to offer the obesity management program.

Although this is a simple illustration, there are still a number of things that the actuary must have available to complete the modeling project. S/he needs data from several sources: the health plan membership characteristics including BMI, estimates of obesity management success (participation, persistence, weight loss) and expected change in health care expenditures associated with BMI change. Some of the data may be available directly from the health plan, but for other parameters s/he will need to search the literature for studies that estimate the parameters of interest.

S/he must also have an easy-to-use modeling software. Software packages are available such as TreeAge (*www.treeage.com*) and Microsoft Excel Add-in forecasting tool Crystal Ball (*www.decisioneering.com/crystal_ball*).

The actuary's next client with an interest in obesity management may be an employer. While a health plan is concerned about making a long-term investment for a membership that turns over, the employer has a stable work force and is concerned not only about the short-term health care expenditures of the active work force, but also the projected expenditures of the growing retiree group. S/he could build on the obesity management model to include additional variables which are of interest to the employer: sick time, productivity and mortality.

This illustration described the use of stochastic modeling for a single program, but the application is easily transferable to an intervention program that has a near-term cost, a long-term benefit and many uncertain but relevant parameters.

Application: Renewal Pricing

Another practical application for stochastic modeling is renewal pricing for a small group block of business. Unlike the previous application which had a near-term cost and a long-term benefit, renewal pricing is a near-term problem. What it shares with the previous application is the existence of several uncertain but relevant parameters. The general modeling strategy described earlier applies to renewal pricing, with the small group acting as the agent in the model. As before, the actuary needs to identify the population of interest (the small groups within the block of business), define the events that can happen to small groups in that population, develop contingency tables or distributions that determine the frequency of the events, model the incidence of events in the population over time and measure outcomes of interest including but not limited to: premium revenue, health care expenditure or group terminations.

The art of renewal pricing aims to achieve a desired overall rate increase by discriminately applying higher than average increases to some groups and lower than average increases to others. Small groups are price sensitive; they will shop for replacement coverage if they consider their renewal increases to be too high. Groups at risk for higher than average health care expenditures are less likely to find better rates and therefore more likely to remain in the block of business. Low risk groups are needed to maintain a financially healthy block of business, and yet these are the groups most likely to shop and transfer their business to a competing insurer.

To illustrate the use of stochastic modeling for renewal underwriting, suppose that traditional analysis determines the need for a 14 percent rate increase for a block of small group business. The 14 percent increase is needed to cover expected health care costs, administrative expenses and profit margin. However, not all groups in the block receive a 14 percent increase: increases range from 7 to 40 percent and in aggregate yield 14 percent overall. The challenge is achieving the required overall increase given the uncertainly as to which groups will stay in the block of business and which will leave. The uncertainty about which groups remain affects both the overall renewal rate needed and the overall rate achieved. Assuming renewal rates are correlated with expected health care costs, if several groups with a 7 percent rate increase lapse, the overall rate needed will probably be higher than the original estimate of 14 percent. But the overall rate achieved should also be higher than planned. A similar, but opposite, effect will result if several of the 40 percent groups lapse. The actuary is concerned not only with achieving a specified renewal rate, but achieving adequate premiums to cover expenses and margin, as well as maintaining a financially healthy block of business. When the set of terminating groups is similar to the initial block, actual results may be similar to expected. However, it is the changing makeup of the block after terminations that leads to uncertainty in the overall renewal rate achieved and the financial health of the block. A key interdependency is between the level of proposed renewal increase and the likelihood of shopping for an alternative carrier. In a deterministic model, the likelihood of a group lapsing would typically be set as a fixed parameter at the outset of the model run. In a stochastic framework, this likelihood can be allowed to vary as a function of other model parameters, thus allowing it to vary probabilistically in relation to the level of proposed renewal increase level. Hence, stochastic iterative modeling may be better at capturing this interdependency than deterministic modeling because it allows for this feedback loop to converge over multiple iterations. In even the simplest example of renewal underwriting, there are several uncertainties which can have a significant impact on outcomes: Will one or more groups shop for replacement coverage? Will those groups that shop for replacement coverage find new coverage and terminate? Will one or more groups terminate for other reasons? What are the future health care expenditures for each group? Will rate relief be granted to some groups with high renewal increases? All of these parameters can be stochastic within a model.

There are several questions to be answered with regard to stochastic modeling. What is the range of outcomes produced by a given rating strategy and what percentage of those outcomes are outside of the insurer's tolerance? In contrast to point estimates from a handful of scenarios, stochastic modeling yields a range of potential outcomes and a frequency of those outcomes are considered to be unacceptable. In application, the renewal rating model would generate several iterations of a rating strategy, often 1,000 iterations are produced in order to obtain stable model estimates. Those 1,000 iterations would be developed by using Monte Carlo techniques to determine actions by each of the groups being simulated. For example, suppose the termination rate for reasons other than price is expected to be 10 percent. A simple Monte Carlo application would generate a yes/no termination action for each group using a 10 percent termination rate. A more sophisticated application would select the termination rate from a pre-defined distribution and then use Monte Carlo techniques to generate each group's action from that rate. And, given enough information on termination, the prevailing termination rate could vary by group characteristics such as group size, duration with the insurer, industry, etc. Similar random variables could be defined for each of the group actions, including the group's future health care expenditures.

Actuaries are particularly good at developing models and using scenarios to test various assumptions about small group behavior. A stochastic simulation model offers an advantage over ad hoc scenario testing because it is a structured framework for renewal rating analysis. At the time this report was written, at least one consulting firm had developed a stochastic simulation modeling tool for small group renewal pricing.[49] Individual group health expenditures were described as stochastic on the consulting firm's Web site, but it was unclear about the number of other group events that were stochastic or whether the parameters themselves were stochastic. Regardless of the details of the cited small group pricing model, it represents a very real practical application of stochastic modeling for health actuaries.

IX. Discussion

A health actuary's main responsibility is to understand and forecast the financial impact of insurance benefit design and medical management changes. Insurance benefit design changes can influence financial results through selection (which members are most attracted to a particular product design) and utilization (determining whether demand for health care services is promoted or discouraged). Medical management initiatives such as expanded treatment coverage, health promotion and disease management all have financial consequences for the actuary's client. In this review of simulation literature, we describe modeling efforts that address each of these health care management changes and measure the financial and health outcomes. Our goals in preparing this review were to expose actuaries to the types of stochastic modeling research published in peer reviewed health journals, suggest ways that actuaries could make use of the modeling techniques or the findings from model applications and increase actuaries' understanding of policy analysis techniques used by health services researchers.

Regardless of modeling methodology, a health actuary is typically providing advice to a payer or provider, hence the actuary's analysis takes the perspective of the client. Many of the articles reviewed for this report take a public policy view, with the analysis taking the perspective of society. Actuaries who may be interested in adapting an analysis that uses a societal perspective to one for use by a client perspective will likely find their client model to be less complex than the model with a societal perspective which frequently encompasses the perspectives of multiple stake-holders (e.g., one entity's costs are another's revenue), benefits and costs that may be more difficult to quantify or measure and sometimes competing values or value systems between different population sub-groups. A client perspective analysis will have many societal concerns removed, leaving only the outcomes of interest to the payer or provider client.

The articles in this review displayed a wide range of quality, as measured by the adequacy of model assumptions, completeness of description of model details, validation of models against defined criteria and appropriateness of the level of model complexity relative to the issue being modeled. Two of the best articles reviewed, from the perspective of completeness and reader comprehension, were the set of articles by Palmer et al. [9, 44] describing their CORE diabetes article. Another very useful article, especially for its introductory remarks contrasting microsimulation and cell-based methods, is the Wolfson[46] article describing the POHEM modeling effort by Statistics Canada. Although the Wolfson article is somewhat dated, information about the POHEM model can be found at the Web site for Statistics Canada at *http://www.statcan.ca/english/spsd/Pohem.htm*.

As we reviewed the selected articles, we noted that over half of them originated outside of the United States. Models were developed in the United Kingdom (Macdonald et al.[10, 11], Cooper et al.[34, 35], Davies et al.[36], Naidoo, et al.[15], and Palmer et al. [9, 44]) or Canada (Muldoon and Stoddart[6], Caro et al.[12], Patten[45], and Wolfson[46]) using statistical databases from their respective countries. Perhaps the nature of national health insurance lends analysts in the United Kingdom and Canada easier access to national data that can facilitate microsimulation modeling. While the United States has a fragmented financing and delivery system for health care, actuaries often address questions from the perspective of one client, and have the advantage of a detailed data set for that client.

Health actuaries have special training for their roles as risk evaluation experts within the insurance industry. It is interesting to note the backgrounds of the first authors of the many articles reviewed in this report. Many are trained in economics (Buchanan, Marquis, Yang and Warner), mathematics (Keeler), health services research (Cooper), health policy (Tengs) or medicine (Kong). Actuaries' unique training combines technical skills with business acumen. As the health care field develops in complexity, actuaries may want to consider collaboration with experts from various other fields to enrich their participation and contribution to solving the many issues of health care.

Actuaries will adopt techniques that add value to their work and benefit their clients. We believe that the use of stochastic simulation modeling is such a technique. The complex world of health care demands answers to challenging questions that actuaries can address using their sophisticated modeling skills, data resources and business training.

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