EVOLUTIONARY METHODOLOGIES FOR ASEISMIC DECISION SUPPORT WITHIN HEALTH CARE FACILITIES AND NETWORKS

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ABSTRACT

Over the past two decades, earthquake engineers have focused considerable attention on the development of new technologies that promise to provide improved seismic performance. This represents the engineering side of the problem. However, the more general objective must be to improve the disaster-resiliency of communities. Achievement of this latter goal not only requires the consideration of the structural and non-structural systems that shape the physical environment, but also the organizational systems that define the economic and social character of the region. As a result, there is a need to model, understand and ultimately direct the behavior of a wide variety of complex multi-scale systems. In particular, we consider health care facilities and networks. Clearly, this represents one of the most critical and complex components in shaping the overall community response following a major disaster. However, our emphasis is on mitigation, rather than response, with the ultimate objective to develop seismic decision support methodologies for individual hospitals, for health care networks and for regional public policy and resource allocation. Evolutionary methodologies may be ideally suited to study and to provide guidance on many of the relevant issues. In this paper, we present an initial evolutionary decision support framework that attempts to integrate a range of sociotechnical models for aseismic decision support. Included are system dynamics economic models for the health care organizations, Gutenberg-Richter geophysical models for the seismic environment, explicit state-space structural dynamics models for building response evaluation, damage models to estimate the effects of extreme events, and risk aversion models to convey societal preferences. We concentrate here especially on the sociotechnical organizational modeling of hospitals.

KEY WORDS

genetic algorithms, decision support, risk aversion, system dynamics, structural dynamics.

INTRODUCTION

The concept of complex adaptive systems, originally formulated by Holland (1962, 1975), has played a prominent role in characterizing the behavior of a broad range of systems. For

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example, both physical and social systems often involve the complicated, nonlinear interaction amongst numerous components or agents. In many cases, the agents are free to aggregate at multiple scales in response to an uncertain or changing environment. As a result, such systems may demonstrate an ability to evolve over time and to self-organize. In the process, these complex adaptive systems may display collective attributes acquired though adaptation that could not be achieved either by individual agents acting independently, or by agents under strict top-down control. Standard examples include a rain forest, the human central nervous system and the local economy. Key characteristics of these complex systems include environmental uncertainty, multi-scale behavior, unsteady temporal response, and large decision spaces. Clearly, from the description just presented, a single critical care facility or critical care network also may be classified as a complex adaptive system.

Holland (1975) developed a unified theory of adaptation applicable for both natural and artificial systems. Ideas from biological evolution were central to his approach. Besides providing a general formalism for studying adaptive systems, this led to the development of evolutionary methods and, more specifically, to genetic algorithms. For the genetic algorithm formalism, let S be the set of possible solutions, E symbolize the class of realizable environments, μ indicate the performance measure, and τ represent the adaptive plan. Then by making selections from a set of operators Ω, the adaptive plan τ produces a sequence of potential solutions $s \in S$ based upon the performance measure μ_e associated with environment $e \in E$. In a genetic algorithm, the individual solutions s are encoded as computational chromosomes, often using a binary string representation. The typical genetic operators contained in Ω include selection, crossover, mutation and replacement. At each generation, the best performing solutions are selected for reproduction. The genetic operators then work to increase the frequency of good qualities contained in the population, while continually exploring the space of possible solutions in S. Figure 1 provides the overall flow of a classical genetic algorithm. Notice, in particular, that a number of stages within the algorithm lend themselves naturally to parallel computing platforms. This is especially true for the fitness evaluation stage, which is often the most computationally demanding task. Further details on genetic algorithms can be found in Holland (1975), Goldberg (1989) and Mitchell (1996).

Although in the original work by Holland the environment may be uncertain, most implementations and applications of genetic algorithms are limited to fixed environments. However, evolutionary methods actually are more appropriate for discovering robust solutions to problems involving uncertainty, ambiguity and risk. Interestingly, these are exactly the types of solutions required for the development of seismically resilient communities.

EVOLUTIONARY ASEISMIC DECISION SUPPORT FRAMEWORK

Figure 2 shows the proposed aseismic decision support methodology. Notice that both physical and sociotechnical models are included. For the geophysical model and earthquake model, we employ the USGS Gutenberg-Richter seismicity database for eastern North America (Frankel, 1995; Frankel et al., 1996) and generate as many ground motions as necessary to evaluate proposed structural design and retrofit options. Following the USGS model, the entire geographical region of eastern North America is subdivided into bins, with each bin representing 0.1 degrees of longitude and latitude. The USGS database then provides Gutenberg-Richter parameters for each bin. We simulate the seismic environment by running Poisson processes in each bin to determine first arrival times T of significant events that may occur during the intended life cycle T_l of the structure. Once magnitude M and epicentral distance R are established for a significant event, the ground motion generation algorithm defined by Papageorgiou (2000) is used to produce an appropriate synthetic accelerogram. This approach is used to simulate n_e environmental realizations independently for each individual structure s at each generation.

Genetic Algorithms
Classical Version (Holland, 1975)

Initialize pool of chromosomes [*Parallel*]
Generation loop [*Serial*]
Chromosome loop [*Parallel*]
Evaluate chromosome fitness
End loop
Apply genetic operators [*Parallel, Serial*]
End Loop
Select best chromosome(s) [*Parallel*]

Figure 1: Genetic Algorithm Flow Diagram

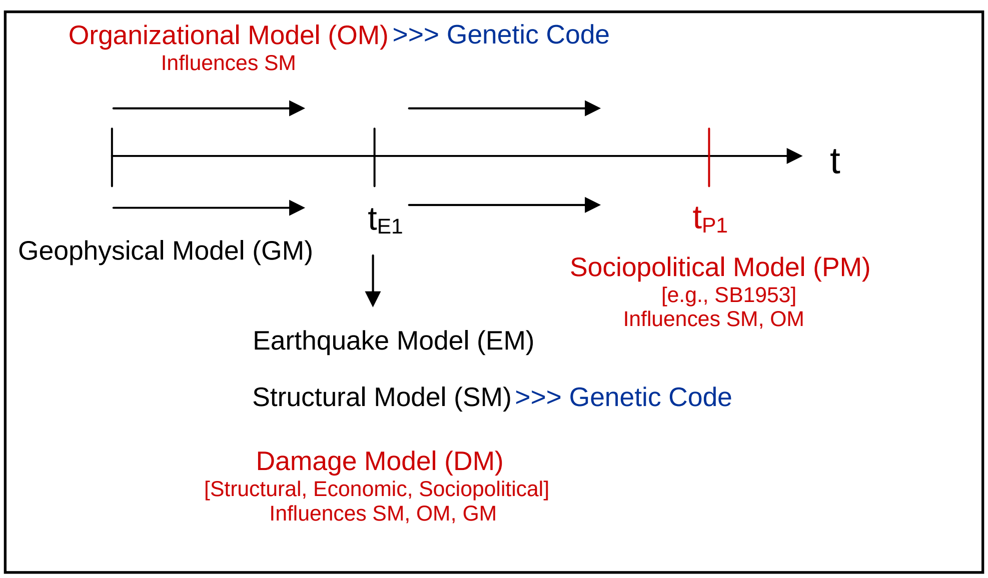

Figure 2: Evolutionary Aseismic Decision Support

Passive energy dissipation systems are now broadly used for the seismic control of civil engineering structures and a wide variety of device types are available, including metallic yielding dampers, friction dampers, viscous fluid dampers and viscoelastic dampers (e.g., Soong and Dargush, 1997; Constantinou et al., 1998). For the present development, we consider design alternatives involving three different types of passive dampers. In order to evaluate structural performance, a lumped parameter structural model is employed. A two-surface cyclic plasticity model in force-displacement space (Constantinou et al., 1998) is used to describe the behavior of the primary structure and metallic dampers. Viscous dampers are represented as purely linear Newtonian devices, with force proportional to velocity. Lastly, viscoelastic dampers are modeled as nonlinear rate-dependent devices based upon a thermally sensitive generalized Maxwell model. For any given design or retrofit option s within the set of possible structures S, the properties for the lumped parameter primary structure and passive element models must be defined at each story. The resulting equations of motion for the n-story passively damped structure are written in state-space form and then solved, along with the applicable constitutive models, using an explicit, adaptive step-size Runge-Kutta method (Press et al., 1992).

In the following sections, complex decision processes are examined within health care organizations. Then a system dynamics organizational model is presented and a numerical example is provided.

ORGANIZATIONAL DECISION SUPPORT

While the evolutionary approach for aseismic design and retrofit mentioned above is useful in distinguishing the various design alternatives, decisions regarding whether or not to retrofit an existing structure are seldom based strictly on engineering grounds. The sociotechnical nature of organizational decision-making must be considered. For the general problem, March and Olsen (1973) proposed a garbage can model for organizational decisions. Recently, Petak and Alesch (2004) have tailored and augmented the March-Olsen model for earthquake hazard risk reduction in healthcare organizations. Based upon their work, there are five prerequisites for organizational action:

(1) The healthcare organization must perceive the seismic risk;
(2) The organization must believe it has an internal locus of control regarding the problem;
(3) The organization must feel that implementing the solution is in its best interests;
(4) The organization must believe that a solution exists to reduce that risk;
(5) Organizational capacity must exist to implement the risk reduction measures.

Petak and Alesch (2004) also emphasize the importance of the temporal dimension of decision-making and the need within the organization to actively seek solutions. This Petak-Alesch descriptive model is very helpful for identifying the prerequisites for organizational action. However, additional qualitative and quantitative models of organizational behavior and performance would be beneficial to support the decision-making process. Currently we are concentrating on the development of succinct differential models using ideas from system dynamics (Forrester, 1961, 1969, 1971) and interacting species formulations (May, 1973).

System dynamics originated in the 1960s with the work of Forrester. System dynamics is a method of analyzing problems in which time is an important factor, and which involves the study of how a system can be defended against, or made to benefit from, the shocks that fall upon it from the outside world. A system dynamics model is a practical, operational decision-making model with interdisciplinary ties. The basic structures of a system dynamics model include stocks, flows, converters and connectors. For critical care facilities, the present system dynamic model utilizes patients, employees, building and equipment, and monetary assets as the four stocks, which are four key variables characterizing organizational behavior. Essentially, the system dynamics model can be represented by a set of ordinary differential equations (ODEs) or stochastic ODEs. The four stocks in the system dynamics model are the four major dependent variables of the ODE set with time as the independent variable. From the system dynamics model, we get a set of simplified dimensionless formulations. This permits analytical investigation using well-established qualitative methods for ODEs. Thus, critical points, limit cycles and stability issues can be analyzed.

As soon as the organizational dynamics model is established, the decision space *S* should be identified. In our model, we focus on three sets of policies, which involve decision-making:

- Policies regarding seismic retrofit: including evaluation frequency (how often should we examine whether or not the facility needs to be retrofitted), retrofit criteria (under what financial conditions can we perform retrofitting), retrofit level (what performance level is expected after retrofitting).
- Policies regarding building and equipment investment: including investment rate, patients vs. building and equipment target ratio and major equipment investment criteria.
- Polices regarding human resource management: including employee hiring rate, patient vs. employee target ratio and employee hiring monetary criteria.

Again, a genetic algorithm is applied to find robust solutions, where each solution corresponds to a specific set of organizational policies. The overall flow of the genetic algorithm for organizational decision support is provided in Figure 3. Currently, the fitness can be defined as one or several of the following objectives: maximizing building and equipment; maximizing monetary assets; maximizing patients served; minimizing accumulated damage; minimizing patient-days lost due to seismic damage.

Evolutionary Organizational Decision Support

Initialize pool of decision sets
Generation loop
    Decision sets loop [*Parallel*]
        Evaluate decision set fitness
    End loop
    Apply genetic operators
End loop
Select best decision set(s)

Figure 3: Evolutionary Organizational Decision Support Flow Diagram

SINGLE HOSPITAL MODEL

The system dynamics model for a hospital can be represented by a set of ordinary differential equations (ODEs). Assuming each hospital has four major dependent variables with time *t* as the independent variables: Patient (*P*), Employee (*E*), Building and equipment (*B*) and Monetary assets (*M*). All of them are normalized by a certain value so that the ODE set is dimensionless to avoid discrepancy due to differing units. This set can be written in stochastic form as follows:

$$dP = c_1 \gamma_{EB} E dt - d_1 \gamma_{EB} P dt \tag{1a}$$

$$dE = c_2 \beta_{EM} E dt - d_2 E dt \tag{1b}$$

$$dB = c_3 \beta_{BM} B dt - d_3 B dt \tag{1c}$$

$$dM = c_4 M dt + c_5 P dt + c_6 d_1 \gamma_{EB} P dt - d_4 E dt - d_5 B dt - d_6 c_3 \beta_{BM} B dt \tag{1d}$$

where

$$\beta_{EM} = (\alpha_E + \frac{\bar{d}_2}{\bar{c}_2}) H(\alpha_E) H(M - M_E) \tag{2a}$$

$$\beta_{BM} = (\alpha_B + \frac{\bar{d}_3}{\bar{c}_3}) H(\alpha_B) H(M - M_B) \tag{2b}$$

where *H(·)* represents the Heaviside function, M_E is the minimum monetary assets to hire employee, M_B is the minimum monetary assets to invest on building and equipment, and

$$\alpha_E = 1 - \gamma_{EE}, \quad \alpha_B = 1 - \gamma_{BB} \tag{3a,b}$$

$$\gamma_{EB} = \left(\frac{E_P B_P}{\hat{E}_P \hat{B}_P} \right)^{1/2}, \quad \gamma_{EE} = \left(\frac{E_P E_B}{\hat{E}_P \hat{E}_B} \right)^{1/2}, \quad \gamma_{BB} = \left(\frac{B_P B_E}{\hat{B}_P \hat{B}_E} \right)^{1/2} \tag{4a-c}$$

with

$$E_P = E / P, \ B_P = B / P, \ E_B = E / B = 1 / B_E \tag{5a-c}$$

while $\hat{E}_P$, $\hat{B}_P$ are target ratios as follows:

$$\hat{E}_P = (E / P)_{target}, \ \hat{B}_P = (B / P)_{target} \tag{6a,b}$$

$$\hat{E}_B = \hat{E}_P / \hat{B}_P = 1 / \hat{B}_E \tag{6c,d}$$

Assuming $P > 0$, $E > 0$ and $B > 0$, c_1, d_1, c_2, ...d_6 are a set of parameters, some of which can be estimated based on the available financial data, others might be set as the policies to be decided by the hospital administration. The parameters are defined as follows:

c_1: Normal patient arrival rate
d_1: Normal patient discharge rate
c_2: Employee hiring rate
d_2: Employee exit rate
c_3: Investment on building and equipment rate
d_3: Building and equipment depreciation rate

c_4: Investment profit rate
c_5: Revenue per in-patient
c_6: Net revenue per discharge
d_4: Average expense per employee
d_5: Building and equipment maintenance fee
d_6: Adjusted building and equipment investment fee

This model defined above only considers routine operation of a hospital. Some abrupt decisions, such as a major investment on building and equipment, a sigificant hiring or lay-off of employees, …, etc. are not taken into account. In addition, extreme events such as earthquakes, epidemics are not yet included in the model.

A NUMERICAL EXAMPLE

The Northridge Hospital Medical Center is located at San Fernando, Los Angeles County, CA. It is a major primary and specialty non-profit acute care hospital with 425 beds and a life-saving trauma unit serving more than 15,600 patients annually. The annual financial and operational data of this hospital from 1995-2003 can be found in the OSHPD (Office of Statewide Health Planning and Development, CA) website. The raw data is then processed in order to extract estimates of the four key system dynamics variables (*i.e.*, *P*, *E*, *B* and *M*). Typical results are displayed in Table 1.

Table 1: The Annual Financial Data (1995-2003) of Northridge Hospital Medical Center

Year	1995	1996	1997	1998	1999	2000	2001	2002	2003
P	334	323	335	337	273	284	295	319	327
E	1,623	1,633	1,413	1,438	1,427	1,241	1,230	1,206	1,551
B(Million dollars)	79.09	76,51	73.17	71.77	70.93	72.25	78.95	86.29	87.12
M(Million dollars)	13.29	11.98	12.91	0.99	-31,38	-27.71	-27.13	-34.89	-32.12

A number of the system dynamics model parameters can be estimated directly from additional data included in the OSHPD database, while others can be established from data-fitting numerical algorithms. For example, here we use the Levenberg-Marquardt Method (Press et al., 1992) to obtain best-fit parameter values. Figure 4a-d presents system dynamics results for four different realizations of the model. However, due to the inherent complexity and uncertainty of the problem, there typically are a number of local extrema in the formulation to determine model parameters. Consequently, an alternative evolutionary algorithm is currently under development for parameter estimation. In any case, once a validated system dynamics model is established, this becomes another component in the overall decision support framework identified in Figures 2 and 3. For decision support at the local hospital level, the decision space incorporates retrofit options, facility investment and expansion/contraction planning. On the other hand, for regional policy support, the decision space involves potential mandated seismic retrofit with or without financial support, along with optional retrofit policies involving incentives. An overall flow diagram for regional policy decision support is provided in Figure 5.

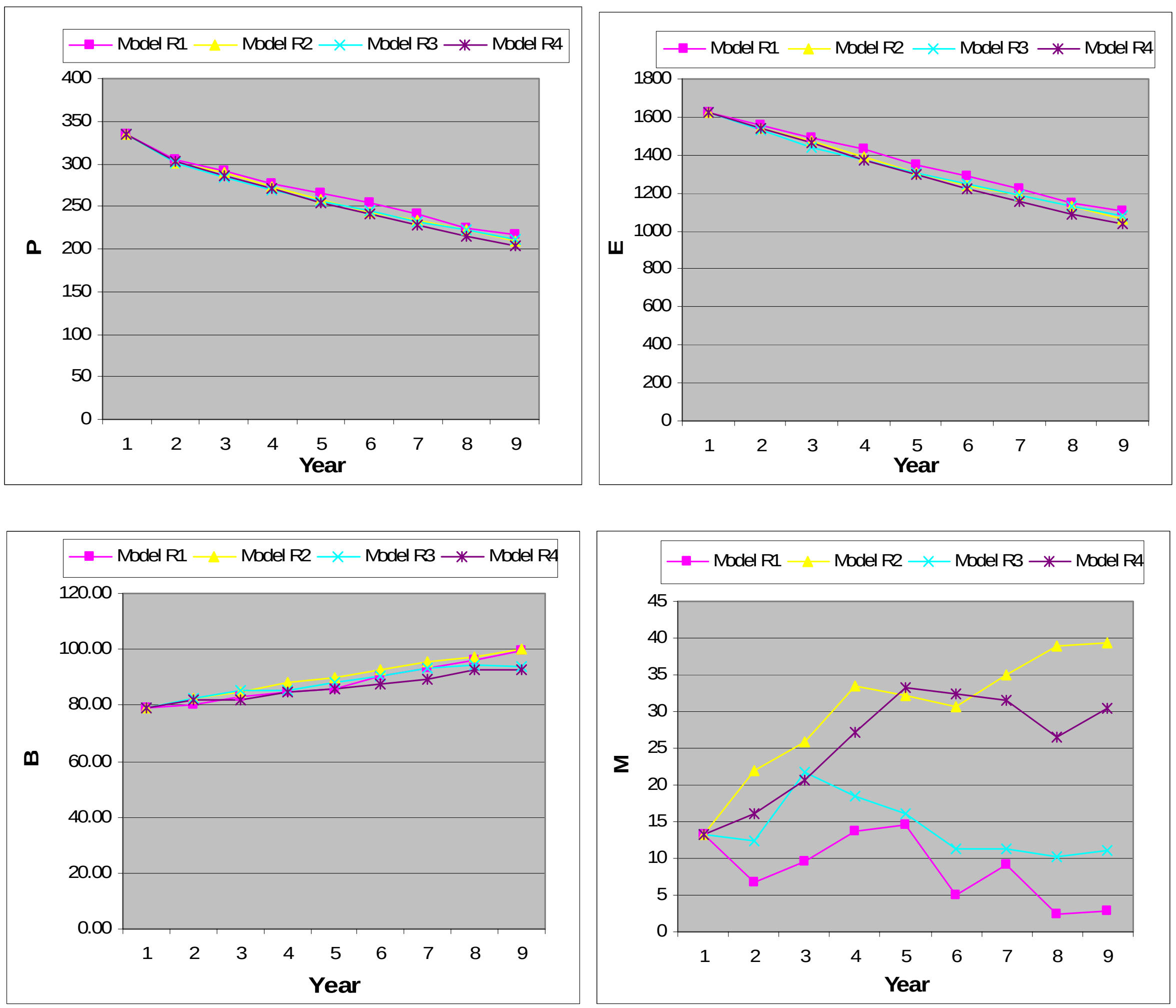

Figure 4: Initial System Dynamics Model Realizations

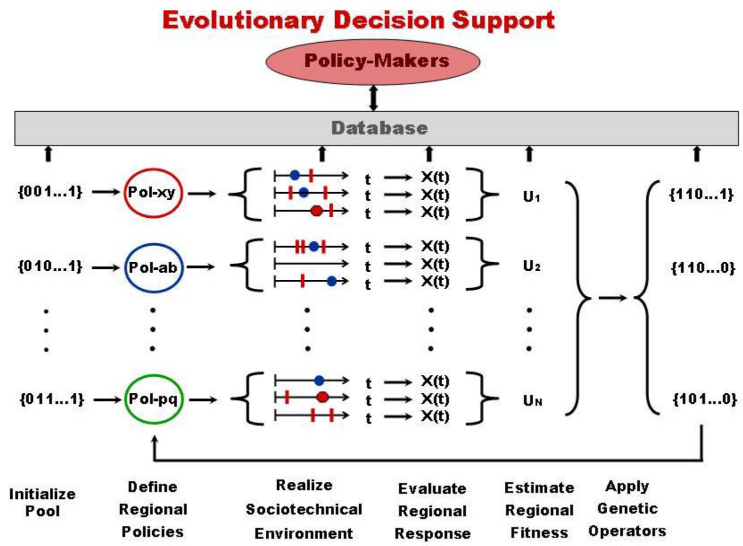

Figure 5: Evolutionary Support for Regional Seismic Policy Decisions

CONCLUSIONS

A general evolutionary framework has been developed to provide support for complex decision processes. This development concentrates on two specific aspects, namely, aseismic design and retrofit decision support and organizational decision support. Within the first domain, we focus on the engineering problem associated with the design of passively damped structural systems and present a computational approach based upon genetic algorithms that has significant potential. In numerous case studies, the system is able to discover robust designs in an uncertain seismic environment. In addition, the algorithms scale favorably with increasing problem size and are naturally parallel. Consequently, continued development of the methodology and the associated software appears to be warranted, particularly in light of the anticipated concurrent advancement of massively parallel computing hardware and grid computing. Furthermore, the extensions of this evolutionary approach to include non-structural components and to address multi-hazard design and retrofit are clearly feasible.

Beyond the engineering aspects of the mitigation problem are many associated socioeconomic issues that must enter into the decision-making process. Consequently, in the present paper, we focus on developing evolutionary formulations for decision support toward seismic risk reduction in critical care organizations. Our present work is concentrated on the development of quantitative organizational models to approximate the overall behavior and to couple with the existing geophysical and structural models in the evolutionary decision support framework. Although some research challenges remain, we believe that this new approach has considerable potential to provide guidance at the level of a single critical care facility and for regional planning of critical care networks.

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