6

Evolutionary Methodologies for Decision Support

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Summary

One of the primary objectives of the MCEER research program is to contribute toward the development of disaster resilient communities. As a result, there is a general need to model, understand and ultimately direct the behavior of a wide variety of complex multi-scale systems. Within the context of a critical care facility, these not only include the structural and non structural systems that shape the physical environment, but also the organizational systems that define the social and economic climate. Evolutionary methodologies (Holland, 1992) may be ideally suited to study and provide guidance for many of these tasks. Robust computational approaches are developed for decision support that incorporates both engineering and sociotechnical aspects. Furthermore, we attempt to create a theoretical and computational framework that may have applicability for complex decision-making in general.

Introduction

During the past two decades, there has been increasing interest in the concept of complex adaptive systems, originally formulated by Holland (1962, 1992). 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. However, from the definition above, a single critical care facility or critical care network also may function as a complex adaptive system. Key characteristics of these complex systems include: Environmental uncertainty; Multi-scale behavior; Large decision space; Temporal dimension.

Tsypkin (1971) presented perhaps the first major work on adaptation in automated systems. His approach was based primarily on the existing methods of optimal control theory. Holland (1992), on the other hand, developed a unified theory of adaptation 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.

In a genetic algorithm, the individual solutions are encoded as computational chromosomes, often using a binary string representation. The typical genetic operators 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. Further details on genetic algorithms can be found in Holland (1992), 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 are more appropriate for discovering robust solutions to problems involving uncertainty, ambiguity and risk. Of course, these are exactly the types of solutions required for the development of seismically resilient communities.

Framework of Evolutionary Methodologies

Figure 1 shows the overall decision support methodology. This methodological framework involves the geophysical (Frankel et al., 1996), earthquake (Papageorgiou, 2000), structural, damage and sociotechnical models.

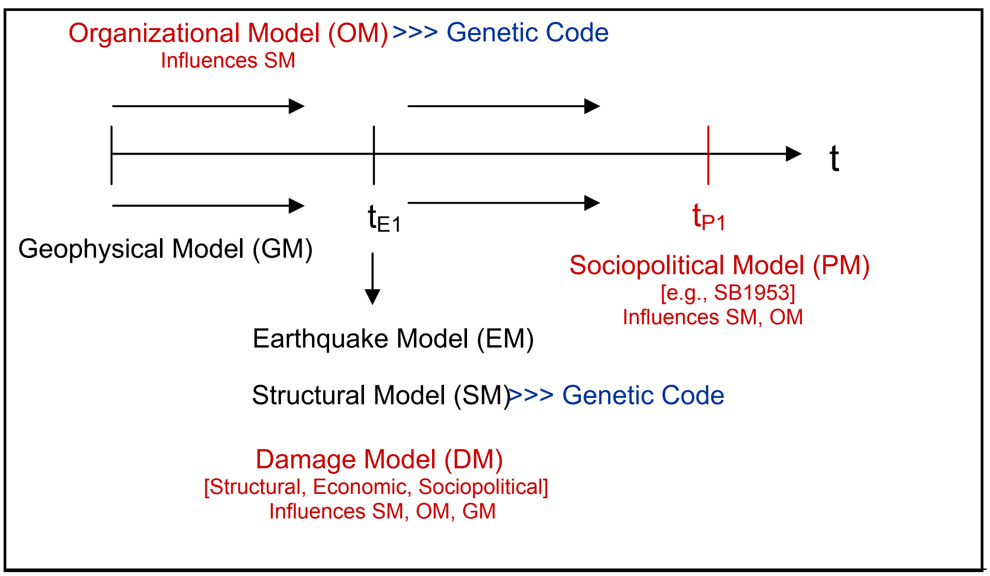

Figure 1. Evolutionary Decision Support

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 of significant events that may occur during the intended life cycle of the structure. Once magnitude and epicentral distance 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 at each generation.

Passive energy dissipation systems are now widely 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). The introduction of these passive energy dissipation concepts and systems presents the structural engineers with considerable freedom in aseismic design and retrofit, however further guidance may be needed to help direct the design process. In order to address this issue, several simplified design procedures have been in development over the past decade. These procedures are oriented mostly toward the design of simple uniform structures. Alternatively, one may attempt to develop new computational approaches that can provide insight into seismic performance, as well as design guidance both for simple structural systems and for complex irregular structures.

Here we adopt this latter approach and continue our development of an evolutionary approach for aseismic design and retrofit. Previous research on the application of genetic algorithms to passively damped structures includes the work by Singh and Moreschi (1999, 2000, 2002), Dargush and Sant (2000, 2002) and Dargush and Green (2002). In particular, the previous work is extended by introducing a parallel genetic algorithm for the design of robust passively damped structures within an uncertain seismic environment.

Organizational Decision Support

While the evolutionary approach for aseismic design and retrofit 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 problems, March and Olsen (1973) proposed a garbage can model for organizational decisions. Recently, Petak and Alesh (2004) have tailored and augmented the March-Olsen model for earthquake hazard risk reduction in healthcare organizations. They 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. Additional qualitative and quantitative models of organizational behavior and performance are needed 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 Jay W. 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 which 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). 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. The critical points, limit cycles and stability issues are analyzed.

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

- Policies regarding close/open wings of the hospital: including close/open criteria (under what conditions can we close/open wings), close/open level (what percentage of the total buildings and equipments should be closed/opened).

Again a Genetic Algorithm is applied to find a robust solution, 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 2. 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.

Evolutionary Organizational Decision Support

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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)
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Figure 2. Evolutionary Organizational Decision Support Flow Diagram

A five story steel frame hospital is used as a preliminary example. We assume the lifetime T_l=50years. For the genetic algorithm, we utilize a string length N_l=26 in a population of n_p=16 policy scenarios for a total of n_g=32 generations and assume maximizing building and equipment is the only measurement of fitness. The dimensionless initial condition is: Initial patients P0 = 1.5, initial employees E0 =1.0, initial building and equipment B0 = 1.25, initial monetary assets M0 = 1.0. Whenever a decision is made to retrofit the hospital, the robust designs of the appropriate level from evolutionary aseismic retrofit design are utilized. Results with six sets of organizational decisions which have highest fitness are shown in Figure 3. We can see decision sets A and D have the highest survival rate above 80%. Decision set A has gone through a large number of realizations and earthquakes, but, the averaged monetary assets are negative. From this simulation, decision set A seems to be a robust decision solution but it might not be suitable for a profitable hospital. However, we should emphasize that this is only a preliminary example intended to illustrate the methodology. Much more work is needed to provide a reliable decision support tool for critical care facilities.

	A	B	C	D	E	F
Realizations:	3392	4928	1088	1408	1472	1152
Fitness :	1.38	1.37	1.36	1.36	1.35	1.35
Retrofit Policy						
Frequency :	8 yr	-	8 yr	2 yr	8 yr	8 yr
Criteria :	R	-	M	R	R	Always
Level :	3	None	3	3	3	3
Building & Equipment Investment Policy						
Rate :	Slow	Slow	Slow	Slow	Slow	Slow
B/P Target :	Highest	Highest	Highest	Highest	Highest	Highest
Threshold :	Lowest	Lowest	Lowest	Lowest	Lowest	Lowest
Human Resource Management Policy						
Rate :	Slow	Slowest	Fast	Slowest	Slowest	Slowest
E/P Target :	Lowest	Lowest	Lowest	Lowest	Lowest	Lowest
Threshold :	Low	Low	Low	Low	Low	Low
Retrofit Status						
Fraction :	0.77	0.00	0.33	0.78	0.75	0.84
Time :	11.59	0.00	19.89	8.05	11.14	8.03
Earthquake Response						
Attempt :	236	317	85	79	97	81
Survive :	193	202	52	66	75	60
Survive Rate:	0.82	0.64	0.61	0.84	0.77	0.74
Overall Performance						
B :	1.38	1.37	1.36	1.36	1.35	1.35
M :	-0.17	0.73	-0.31	0.65	0.63	0.55
P Admit :	6.27	6.22	6.34	6.12	6.07	6.02
Damage :	0.03	0.07	0.09	0.02	0.04	0.06

Figure 3. Organizational decision support preliminary example

Conclusion

A general evolutionary framework has been developed to provide support for complex decision processes. Beyond the engineering aspects of the mitigation problem, there are many associated socioeconomic issues that must enter into the decision-making process. Consequently, 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 many 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 also for regional planning of critical care networks.

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