Evolutionary Methodologies for Decision Support

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ABSTRACT

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. In this paper, we concentrate on two aspects of the overall problem, namely, aseismic design and retrofit decision support and organizational decision support. Robust computational approaches are developed for decision support that incorporate 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 through 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; Multiscale 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.

Within the Holland genetic algorithm formalism, let $S$ be the set of possible solutions, $E$ symbolize the class of realizable environments, $\mu$ indicate the performance measure, and $\tau$ represent the adaptive plan. Then by making selections from a set of operators $\Omega$, the adaptive plan $\tau$ produces a sequence of potential solutions $s \in S$ based upon the performance measure $\mu$, 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 $\Omega$ 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 there are a number of stages within the algorithm that 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 (1992), Goldberg (1989) and Mitchell (1996).

<table>
<thead>
<tr>
<th>Genetic Algorithms</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Classical Version (Holland, 1992)</strong></td>
</tr>
<tr>
<td>Initialize pool of chromosomes [Parallel]</td>
</tr>
<tr>
<td>Generation loop [Serial]</td>
</tr>
<tr>
<td>Chromosome loop [Parallel]</td>
</tr>
<tr>
<td><strong>Evaluate chromosome fitness</strong></td>
</tr>
<tr>
<td>End loop</td>
</tr>
<tr>
<td>Apply genetic operators [Parallel, Serial]</td>
</tr>
<tr>
<td>End Loop</td>
</tr>
<tr>
<td>Select best chromosome(s) [Parallel]</td>
</tr>
</tbody>
</table>

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

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.

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). So for the structural model, a lumped parameter
representation for both the primary structure and passive elements 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. The 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 two sections, a pair of specific complex decision processes is addressed. The first is an engineering design problem associated with the selection of passive energy dissipation elements for building structures under seismic loading, while the second involves a preliminary look at the broader sociotechnical problem.

### ASEISMIC DESIGN AND RETROFIT DECISION SUPPORT

The introduction of these passive energy dissipation concepts and systems presents the structural engineer 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.

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**Evolutionary Aseismic Design and Retrofit**

- Initialize pool of structures
- Generation loop
  - Structure loop \([Parallel]\)
  - **Evaluate Structure fitness via transient dynamic analysis**
  - End loop
  - Apply genetic operators
- End Loop
- Select best structure(s)

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**Figure 3. Evolutionary Aseismic Design and Retrofit Flow Diagram**

The overall flow of the genetic algorithm for aseismic design and retrofit is provided in Figure 3. In each generation, a population of individual structures \( s \in S \) is defined and evaluated in response
to ground motions that are realized in association with an environment $e \in E$. The primary structure may contain a number of metallic yielding dampers, viscous fluid dampers and/or viscoelastic solid dampers over a range of sizes. A binary code in the chromosome of each individual structure $s \in S$ determines the specific design. Cost and structural performance are used to evaluate the fitness of each structure in the population. Then the individual structures compete for survival within the uncertain environment. The fitness values, along with random genetic operators modeling selection, crossover and mutation processes, define the makeup of the next generation of structures. While, in the present implementation, generations must be processed sequentially, evaluations within a generation can be performed in parallel. Furthermore, multiple simulations with different initial seeds can be run simultaneously in a massively parallel computing environment.

In our present system, performance is judged by conducting nonlinear transient dynamic analyses for ground motions that are consistent with the USGS seismicity model for eastern North America (Frankel, 1995; Frankel et al., 1996; Papageorgiou, 2000). The structural analysis utilizes an explicit state-space transient dynamics research code (tda), while the implementation of the genetic algorithm controlling the design evolution is accomplished within Sugal (Hunter, 1995).

**Computational Simulations**

The evolutionary aseismic retrofit strategy is applied to a hypothetical five-story steel frame hospital located in Memphis, TN. The baseline frame model has uniform story stiffness and weights, such that $k_1 = \ldots = k_5 = k$ and $W_1 = \ldots = W_5 = W$. Furthermore, $k$ and $W$ are selected to produce a fundamental period $T_1 = 1$ sec and the second period of oscillation $T_2 = 0.34$ sec. Rayleigh damping is ignored, however hysteretic dissipation due to inelastic response is included.

Assuming only viscous dampers are available. For the damper size parameters, we let $\Gamma_B = 0.5$, $\Gamma_C = 1$, $\Gamma_D = 2$. Damper cost depends on the size. The four possible alternatives at each story are as follows: no damper, size $\Gamma_B$ damper, size $\Gamma_C$ damper or size $\Gamma_D$ damper. For the genetic algorithm, we utilize a string length $N = 10$ in a population of $n_p = 32$ structures for a total of $n_g = 64$ generations. Each structure is subjected to a maximum of $n_e = 128$ temporal realizations of duration $T_l$ at each generation.

Damage is assumed to be related to interstory drifts and story accelerations. We set up three different target performance levels for retrofitting. Table 1 shows the assumed limit states of interstory drift and story acceleration for different retrofit levels.

<table>
<thead>
<tr>
<th>Retrofit level</th>
<th>Interstory drifts (mm)</th>
<th>Story acceleration (g)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>75</td>
<td>0.75</td>
</tr>
<tr>
<td>2</td>
<td>50</td>
<td>0.50</td>
</tr>
<tr>
<td>3</td>
<td>25</td>
<td>0.25</td>
</tr>
</tbody>
</table>

The fitness can be defined as benefits minus damper cost. If a limit state is exceeded during the analysis, a damage cost is imposed with added provision that the fitness must remain non-negative.

Figure 4 shows the three most robust retrofit designs with highest fitness in each of the three retrofit levels. The radius of the rings corresponds to damper size. Notice that each of the designs for retrofit level 1 and level 2 experienced over four hundred earthquakes with survival rates well above
90% and fitness above nine hundred. For retrofit level 3, because of stricter target interstory drift and story acceleration, survival rates decrease to 85%~90% and fitness decrease to around 840.

Figure 4. Aseismic retrofit design for a five story steel frame

ORGANIZATIONAL DECISION SUPPORT

While the evolutionary approach for aseismic design and retrofit developed here 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 Alesh (2004) have tailored and augmented the March-Olsen model for earthquake hazard risk reduction in healthcare organizations. There are five prerequisites for organizational action:

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

Petak and Alesh (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. 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.
• Policies 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 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 5. Notice the similarity with Figure 4. 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

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 5. Evolutionary Organizational Decision Support Flow Diagram

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
<th>E</th>
<th>F</th>
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<td>1088</td>
<td>1408</td>
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<td>Fitness</td>
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<td>1.36</td>
<td>1.36</td>
<td>1.35</td>
<td>1.35</td>
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</table>

**Retrofit Policy**

<p>| | | | | | |</p>
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<tbody>
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<td>-</td>
<td>8 yr</td>
<td>2 yr</td>
<td>8 yr</td>
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<tr>
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<td>R</td>
<td></td>
<td>M</td>
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<td>R</td>
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**Building & Equipment Investment Policy**

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<th>Slow</th>
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<th>Slow</th>
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<tbody>
<tr>
<td>B/P Target</td>
<td>Highest</td>
<td>Highest</td>
<td>Highest</td>
<td>Highest</td>
<td>Highest</td>
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<tr>
<td>Threshold</td>
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<td>Lowest</td>
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**Human Resource Management Policy**

<table>
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<th>Slow</th>
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<th>Fast</th>
<th>Slowest</th>
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</thead>
<tbody>
<tr>
<td>E/P Target</td>
<td>Lowest</td>
<td>Lowest</td>
<td>Lowest</td>
<td>Lowest</td>
<td>Lowest</td>
<td>Lowest</td>
</tr>
<tr>
<td>Threshold</td>
<td>Low</td>
<td>Low</td>
<td>Low</td>
<td>Low</td>
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**Retrofit Status**

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<tr>
<th></th>
<th>0.77</th>
<th>0.00</th>
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<th>0.78</th>
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<tr>
<td>Time</td>
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<td>0.00</td>
<td>19.89</td>
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**Earthquake Response**

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<tr>
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<th>236</th>
<th>317</th>
<th>85</th>
<th>79</th>
<th>97</th>
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<tbody>
<tr>
<td>Attempt</td>
<td>193</td>
<td>202</td>
<td>52</td>
<td>66</td>
<td>75</td>
<td>60</td>
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<tr>
<td>Survive</td>
<td>0.82</td>
<td>0.64</td>
<td>0.61</td>
<td>0.84</td>
<td>0.77</td>
<td>0.74</td>
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</table>

**Overall Performance**

<table>
<thead>
<tr>
<th></th>
<th>1.38</th>
<th>1.37</th>
<th>1.36</th>
<th>1.36</th>
<th>1.35</th>
<th>1.35</th>
</tr>
</thead>
<tbody>
<tr>
<td>B</td>
<td>-0.17</td>
<td>0.73</td>
<td>-0.31</td>
<td>0.65</td>
<td>0.63</td>
<td>0.55</td>
</tr>
<tr>
<td>M</td>
<td>6.27</td>
<td>6.22</td>
<td>6.34</td>
<td>6.12</td>
<td>6.07</td>
<td>6.02</td>
</tr>
<tr>
<td>P Admit</td>
<td>0.03</td>
<td>0.07</td>
<td>0.09</td>
<td>0.02</td>
<td>0.04</td>
<td>0.06</td>
</tr>
<tr>
<td>Damage</td>
<td>0.03</td>
<td>0.07</td>
<td>0.09</td>
<td>0.02</td>
<td>0.04</td>
<td>0.06</td>
</tr>
</tbody>
</table>

Figure 6. Organizational decision support preliminary example
The five story steel frame hospital is used again as a preliminary example. We assume the lifetime \( T_l = 50 \) years. For the genetic algorithm, we utilize a string length \( N_s = 18 \) 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 \( P_0 = 1.5 \), initial employees \( E_0 = 1.0 \), initial building and equipment \( B_0 = 1.25 \), initial monetary assets \( M_0 = 1.0 \). Whenever a decision is made to retrofit the hospital, the robust designs of the appropriate level from Figure 4 are utilized. Results with six sets of organizational decisions which have highest fitness are shown in Figure 6. 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.

CONCLUSION

A general evolutionary framework has been developed to provide support for complex decision processes. Here we concentrate on two specific aspects, namely, aseismic design and retrofit decision support and organizational decision support. Within the first domain, we concentrate 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. 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, 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.

REFERENCES


London and New York.