Is it Possible to Generate Good Earthquake Risk Models Using Genetic Algorithms?

Claus Aranha[1], Yuri Cossich Lavinas[2], Marcelo Ladeira[2] and Bogdan Enescu[3]
[1]*University of Tsukuba, Graduate School of Systems and Information Engineering, Tsukuba, Japan*
[2]*University of Brasilia, Department of Computer Science, Brasilia DF, Brazil*
[3]*University of Tsukuba, Faculty of Life and Environmental Sciences, Tsukuba, Japan*

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Abstract: Understanding the mechanisms and patterns of earthquake occurrence is of crucial importance for assessing and mitigating the seismic risk. In this work we analyze the viability of using Evolutionary Computation (EC) as a means of generating models for the occurrence of earthquakes. Our proposal is made in the context of the ”Collaboratory for the Study of Earthquake Predictability” (CSEP), an international effort to standardize the study and testing of earthquake forecasting models. We use a standard Genetic Algorithm (GA) with real valued genome, where each allele corresponds to a bin in the forecast model. The design of an appropriate fitness function is the main challenge for this task, and we describe two different proposals based on the log-likelihood of the candidate model against the training data set. The resulting forecasts are compared with the Relative Intensity algorithm, which is traditionally employed by the CSEP community as a benchmark, using data from the Japan Meteorological Agency (JMA) earthquake catalog. The forecasts generated by the GA were competitive with the benchmarks, specially in scenarios with a large amount of inland seismic activity.

1 INTRODUCTION

Earthquakes pose a great risk for human society, in their potential for large scale loss of life and destruction of infra-structure. In the last decade, large earthquakes such as Sumatra (2004), Kashmir (2005), Sichuan (2008) and Touhoku (2011, shown in Figure 1) caused terrible amounts of casualties.

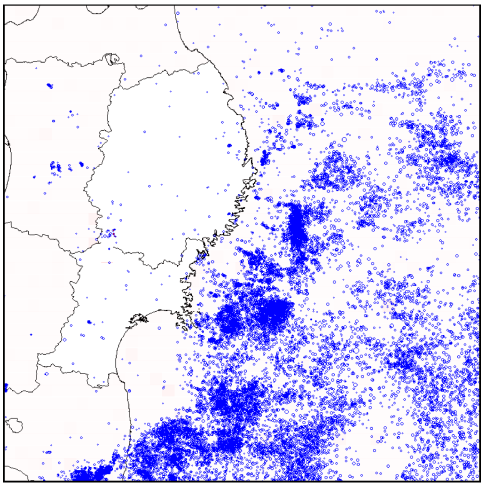

Figure 1: Seismic Activity in Eastern Japan in 2011. Each circle represents one earthquake.

It is crucially important to understand the patterns and mechanisms behind the occurrence of earthquakes. This knowledge may allow us to create better seismic risk forecast models, indicating which regions show a higher probability of earthquake occurrence at certain periods in time. Such information can be put to good use for mitigating damage through urban planning, civil engineering codes, emergency preparedness, et cetera.

Earthquake “prediction” is a polemic subject. No research so far has even come close to suggesting that individual large scale earthquakes can be predicted with any sort of precision. On the other hand, it is clear that at the very least earthquakes do cluster in time and space. There is a lot of value behind the study of earthquake mechanisms, with the goal of generating statistical models of earthquake risk (Saegusa, 1999). Accordingly, in this paper we focus on models of earthquake risk, and not on earthquake prediction.

Surprisingly enough, applications of Evolutionary Computation (EC) for the problem of earthquake

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forecasting have been few and far between. Given that EC has some times managed to find better solutions than humans for hard problems (Koza et al., 2003), we wonder if Artificial Evolution might not be able to find new ideas that improve our understanding of earthquakes and their processes.

With this in mind, the goal of this paper is to explore the suitability of Evolutionary Computation to the problem of generating earthquake forecast models. We aim to provide two main contributions:

1. Outline the earthquake forecast problem, which can be used as a foundation for other researchers who wish to contribute to this field.
2. Show that Evolutionary Computation is a promising methodology for the creation of earthquake forecast models, providing the motivation for further research in this direction.

It is important to note that our goal is not to generate an "earthquake alarm system". Rather, we use Evolutionary Algorithms to find patterns that can be useful for further understanding the mechanisms behind earthquake occurrence.

A common problem with applications of evolutionary algorithms is how to compare different methods, developed by different groups with different testing protocols, in a scientific fashion. We survey and summarize the "best practices" for the studying and testing of earthquake forecast models, as suggested by the *Collaboratory for the Study of Earthquake Predictability* (CSEP), an international partnership to promote rigorous study of the feasibility of earthquake forecasting and predictability.

Based on this framework, we design and implement a simple Genetic Algorithm for earthquake forecast modeling (*GAModel*). We compare forecasts generated by the GAModel with the Relative Intensity algorithm (RI) and an information-less forecast. These systems are applied on the earthquake catalog from the Japanese Meteorological Agency (JMA), using event data from 2005 to 2012. The forecasts are analyzed by their log-likelihood values compared to the actual data, as suggested in the Regional Earthquake Likelihood Model (RELM), and by the Area Skill Score (ASS) test.

The forecasts created by the GAModel were generally competitive in relation to the RI algorithm, specially in scenarios with large amount of inland seismic activity. We discuss some of the strong and weak points identified from the experiment. The results overall show that while there is vast room for improvement, Evolutionary Algorithm approaches definitely have potential in this field.

This paper is an extension of the ideas initially proposed in (Aranha and Enescu, 2014). In the current work, we show the set-up of the genetic algorithm used in great detail, including the discussion of two fitness function. A larger number of earthquake scenarios is considered, with the addition of offshore earthquakes. We also make a detailed presentation of the problem, to those researchers not familiar with this field.

The paper is organized as follows: in Section 2 we detail the earthquake forecast problem, and the CSEP framework. Section 3 reviews applications of Evolutionary Computation in the context of seismology research. In Section 4 we detail the proposed Genetic Algorithm system for generating earthquake forecasts. In Section 5 we present the results of the comparisons between this system and the RI algorithm. In Section 6 we discuss the implications of the results and conclude the paper.

2 THE EARTHQUAKE FORECASTING PROBLEM

In the field of seismology, there is a large number of model proposals for earthquake forecasting. These proposals range from methods based on geophysical principles to purely statistical algorithms.

In this context, the *Collaboratory for the Study of Earthquake Predictability* (CSEP)[1] proposes a methodology for rigorous scientific testing of these many different models.

This testing happens mainly in the shape of distributed virtual laboratories (Nanjo et al., 2011). Multiple research groups will submit their forecast models. These models are be compared against future earthquake event data using standardized testing protocols. The testing suite used in these comparisons is made publicly available by the CSEP, so that researchers can develop and test their models beforehand.

In many application domains, the lack of an unified testing protocol means that comparing methods developed by different research groups can be a great burden. The CSEP framework allows us to objectively and consistently compare our proposed algorithms with previous approaches.

2.1 Earthquake Forecast Model

In the CSEP framework, a forecast exists in reference to a geographical region, a start date and an end date. The forecast will estimate the number (and sometimes

[1] http://www.cseptesting.org

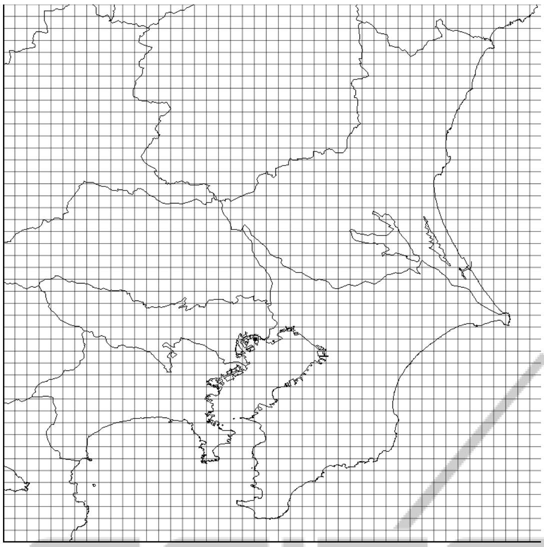


Figure 2: Target area for the Kanto region and its bins.

the magnitude) of earthquakes that happens in the target region during the target time interval.

A forecast is divided into bins. Each bin represents a non-overlapping geographical interval within the target region, and sometimes also a magnitude interval.

For example, in this paper we define the "Kanto" region as as the area covered by latitude N34.8 to N36.3, and longitude E138.8 to E140.3. This area is divided into 2025 bins (a grid of 45x45 squares). Each bin has an area of approximately $25km^2$ (Figure 2).

For each bin in the forecast we define a number of expected earthquakes. This number must be a positive integer. A good forecast is one where the number of estimated earthquakes in each bin corresponds to the actual number of earthquakes that occurs in that bin during the target time interval.

2.2 Comparison Testing

The CSEP framework uses six different tests to compare earthquake forecasts. These are divided into two groups: log-likelihood based tests, and alarm based tests.

The first group is based on the analysis of the similarity between the forecast and the actual earthquake catalog, following the Regional Earthquake Likelihood Model (RELM) (Schorlemmer et al., 2007). The log likelihood of the forecast, given the actual data, is calculated using a Poisson's probability distribution. From this data, three tests are defined. The *L-test* compares the difference between the log-likelihood of the forecast against the actual data, and the log-likelihood of the forecast against itself. The *N-test* tests whether the forecast is predicting too many or too few events in total, and the *R-test* provides an algorithm for the statistical testing of multiple forecasts at once.

These tests require that all forecasts under comparison have the same number and size of bins. Also, due to the way the log likelihood is calculated, they pose a restriction on the forecast: if any one bin in the forecast has zero earthquakes, while the corresponding bin in the data has one or more events, the entire forecast is discarded.

Alarm based tests, on the other hand, use a threshold analysis (Zechar and Jordan, 2010). For a given forecast a numerical threshold is decided: all bins with forecast values above the threshold are added to an alarm set. Earthquakes that fall in this alarm set are counted as hits, while those falling outside the alarm set are counted as misses. Alarm based tests rely on two values: a miss rate v, the proportion of misses to the total number of earthquakes; and the coverage rate τ, the smallest alarm set necessary to achieve v.

Three alarm based tests are defined. The *Molcham Diagram* draws a path of v and τ based on varying values of the threshold. The *Area Skill Score (ASS)* is defined as the area of the curve under the Molcham diagram, and can be used to summarize the information from the Molcham diagram as a single number. Finally, a *Receiver Operation Characteristic (ROC)* analysis can be done from v and τ. Alarm based tests can compare forecasts with different bin sizes, but they do not directly take into account the total number of earthquakes on the forecast, or the data.

3 EVOLUTIONARY COMPUTATION FOR EARTHQUAKE RISK ANALYSIS

Reports of the application of Evolutionary Computation and related methods for the generation of earthquake forecasts are rather sparse. One such approach is described by Zhang and Wang (Zhang and Wang, 2012). They use Genetic Algorithms to fine tune an Artificial Neural Network (ANN), and use this system to produce a forecast. Unfortunately that paper did not provide enough information to reproduce the proposed GA+ANN system or their results. Zhou and Zu (Zhou and Zhu, 2014) also recently proposed a combination of ANN and EC, but their system only forecasts the magnitude parameter of earthquakes.

On the other hand, there are quite a few works using Evolutionary Computation methods for the estimation of parameter values in seismological models. These models are used to describe and understand particular characteristics of earthquakes or earthquake activity.

For example, there are many examples of using Evolutionary Computation to estimate the peak ground acceleration of seismically active areas (Kermani et al., 2009; Cabalar and Cevik, 2009; Kerh et al., 2010). Ramos (Ramos and Vázques, 2011) used Genetic Algorithms to decide the location of sensing stations in a seismically active area in Mexico. Nicknam et al. (Nicknam et al., 2010) and Kennett and Sambridge (Kennet and Sambridge, 1992) used evolutionary computation to determine the Fault Model parameters (such as epicenter location, strike, dip, etc) of a given earthquake.

4 A FORECAST MODEL USING GENETIC ALGORITHMS

To investigate the ability of Evolutionary Computation to generate earthquake forecast models, we design and test a simple Genetic Algorithm. We call this system the *GAModel*.

An individual's genome in GAModel encodes a forecast model as defined in the CSEP framework (see Section 2.1). The population is trained on earthquake occurrence data for a fixed training period, which is anterior to the target test period. After the stopping criterion is reached, the best individual is taken as the final forecast.

By encoding the entire forecast as the genome of one individual, we identify two concerns that must be addressed by any EC-based approach: First, as forecast models normally include a few thousand bins, an individual's genome will be correspondingly large. Evolutionary operators and parameters must be chosen to guarantee convergence in a reasonable time frame.

Second, the design of the fitness function deserves a lot of attention, to avoid the risk of over fitting the system to the training data.

4.1 Genome Representation

In GAModel, each individual represents an entire forecast model. The genome is a real valued array X, where each element corresponds to one bin in the desired model (the number of bins n is defined by the problem). Each element $x_i \in X$ takes a value from $[0,1)$. In the initial population, these values are sampled from a uniform distribution.

In the CSEP framework, a model is defined as a set of integer valued expectations, corresponding to the number of earthquakes for each bin. To convert from the real valued chromosome to a integer forecast, we use a modification of the Poisson deviates extraction algorithm from (Press et al., 2007) (Chapter 7.3.12).

Algorithm 1: Obtain a Poisson deviate from a $[0,1)$ value.

Parameters $0 \leq x < 1, \mu \geq 0$
$L \leftarrow \exp(-\mu), k \leftarrow 0, prob \leftarrow 1$
repeat
  increment k
  $prob \leftarrow prob * x$
until $prob > L$
return k

In Algorithm 1, x is the real value taken from the chromosome, and μ is the average number of earthquakes observed across the entire training data. Note that in the original algorithm, $k-1$ is returned. Because the log likelihood calculation used for model comparison discards forecasts that estimate zero events in bins where earthquakes are observed, we modify the original algorithm to make sure all bins estimate at least one event.

4.2 Fitness Function

Usually, the main challenge when applying an Evolutionary Computation method to any new application domain is the definition of an appropriate fitness function. Accordingly, a large part of our effort was used to define a good fitness function for GAModel.

We describe two candidate fitness functions. The first one is a direct application of the log likelihood definition for earthquake forecast. Because this fitness function resulted in an excessive amount of over fitting, we describe a second fitness function that breaks the training data set into smaller data sets in order to avoid this problem.

4.2.1 Simple Log Likelihood Fitness Function

This fitness function uses the log-likelihood between the forecast generated by an individual and the observed earthquakes in the training data, as described by Schorlemmer et al. (Schorlemmer et al., 2007). In simple terms, the log likelihood is a measure of how close a forecast is to a given data set.

Let $\Lambda = \{\lambda_1, \lambda_2, \ldots, \lambda_n | \lambda_i \in \mathbb{N}\}$ be a forecast with n bins. In this definition, λ_i is the number of earthquakes that is forecast to happen in bin i. To derive Λ_X from an individual $X = \{x_1, x_2, \ldots, x_n | 0 \leq x_i < 1\}$, we calculate each λ_i from x_i using Algorithm 1.

Now, let $\Omega = \{\omega_1, \omega_2, \ldots, \omega_n | \omega_i \in \mathbb{N}\}$ be the observed numbers of earthquakes for each bin i in the training data. The log likelihood between an individual's forecast Λ_X and the observed data Ω is calculated as:

$$L(\Lambda_X|\Omega) = \sum_{i=0}^{n} -\lambda_i + \omega_i * \ln(\lambda_i) - ln(\omega_i!) \quad (1)$$

There are two special cases that arise when any $\lambda_i = 0$. If $\lambda_i = 0$ and $\omega_i = 0$, then the value of the sum for that element is 1. If $\omega_i > 0$, then $L(\Lambda_X|\Omega) = -\infty$ and the forecast must be discarded. For more details on this, see (Schorlemmer et al., 2007).

In the Simple Log Likelihood fitness function, the value of $L(\Lambda_X|\Omega)$ is taken directly as the fitness value of the individual.

Early testing with the Simple Log Likelihood function showed that GAModel had a very strong tendency to over fit to the training data. This is natural, since there are differences between the seismicity of a larger period and a shorter one. To solve this problem, we used the fitness function shown in the next section.

4.2.2 Time-slice Log Likelihood Fitness Function

In the time-slice log likelihood fitness function we break up the training data set into smaller slices. These slices are based on the chronology of the earthquakes contained in the training catalog. The duration of each slice is the same as the duration of the target interval (the test data).

Let's consider an example: the target period for the forecast is one year, from 1/1/2014 to 1/1/2015, and the training data is taken from the 10 year period between 1/1/2004 and 1/1/2014. To apply the time-slice log likelihood fitness function, we divide the training data into ten 1-year slices, from 2004 to 2005, 2005 to 2006, and so on.

When an individual X is evaluated, we calculate the log likelihood of its forecast Λ_X against each of the time slices $(\Omega_{2004}, \Omega_{2005}, \ldots, \Omega_{2013})$. We use the lowest log likelihood value from among all the slices as the fitness value of X.

The idea behind this fitness function is that the catalog data available for training will normally span a period of time much longer than the desired forecast. By breaking the training data into smaller periods, we are trying to make the evolutionary algorithm learn any time-repeating pattern that might exist in the data. We choose the smallest log likelihood from the time slices in order to make sure that the evolution process favors solutions that try to solve all slices equally.

4.3 Evolutionary Operators and Parameters

GAModel uses a regular generational genetic algorithm. For selection, we use Elitism and Tournament selection.

We use a simple Uniform Crossover for the crossover operator. If a gene's value falls outside the $[0,1)$ boundary, it is truncated to these limits. For the mutation operator, we sample entirely new values from $[0,1)$ for each mutated chromosome.

Table 1: Parameters used in GAModel.

Population Size	500
Generation Number	100
Elite Size	1
Tournament Size	50
Crossover Chance	0.9
Mutation Chance (individual)	0.8
Mutation Chance (chromosome)	(genome size)$^{-1}$

The parameters used for the evolutionary computation are described in Table 1. Because our focus is to show the viability of Evolutionary Algorithms for this application problem, we are not yet particularly concerned with the convergence speed of the system. Accordingly, not a lot of effort was spent fine tuning these parameter values. These values were chosen instead by trial and error on a data region not used in the experiments of Section 5.1, until an acceptable convergence time was found.

It would be very interesting to perform an extended effort into identifying the sensibility of each parameter above to the current application domain. For example, while in this work we are worried about analyzing the influence of the fitness function in the degree of over fitting in the results, a precise control of the value for the tournament size parameter might also have an effect in this regard.

5 EXPERIMENTS

To analyze the performance of the forecasts generated by the GAModel, we execute a simulation experiment. In this simulation, the GAModel evolves using a training data set, and the resulting forecast is analyzed against a test data set. These results are compared against two other forecasts: an "unskilled" model, which randomly guesses the forecast (Figure 4), and a forecast generated by the Relative Intensity (RI) algorithm, regarded as a natural reference for comparative tests with earthquake forecast models (Nanjo, 2011).

5.1 Experimental Data

The data used in these experiments comes from the Japan Meteorological Agency's (JMA) catalog. The catalog lists earthquakes recorded by the sensing station network in Japan. For each earthquake, the following values are given: time of occurrence, magnitude, latitude and longitude and depth of the hypocenter.

To avoid issues related to the incompleteness of the catalogue for very weak or very deep earthquakes, we consider only events with magnitude above 2.5 and depth less than 100km. We consider earthquakes recorded in the period between 2000 and 2013. This accounts for more than 220.000 earthquakes in the Japanese archipelago.

To achieve a better understanding of the forecasting power of GA models, we define four areas (scenarios) to focus in our experiment. Figure 3 shows where these four areas are located within Japan. Three of these areas (Kanto, Touhoku and Kansai), contain mainly inland earthquakes, which are considered to follow more stable patterns. The fourth area (East Japan) includes also many off-shore earthquakes. To make it easier to compare the results for each area, we choose the bin size so that the total number of bins is within the same order of magnitude in all areas.

1. **Kanto:** Kanto is the area at and nearby Tokyo. There is a large amount of seismic activity in the target period. In this study, we define this region as starting at N34.8,W138.8, with 2025 bins arranged in a 45x45 grid. Each bin corresponds to a square with 25km^2.
2. **Kansai:** The Kansai area includes Kyoto, Osaka, Kobe and nearby cities. This area shows a relatively lower amount of seismic activity in the period considered. We define this region as starting at N34,W134.5, with 1600 bins arranged in a 40x40 grid. Each bin corresponds to a 25km^2 square.
3. **Touhoku:** The Touhoku region is defined as the northern provinces of the main island. It shows some clusters of seismic activity during the period studied. We define this region as starting at N37.8,W139.8, with 800 bins arranged in a 40x20 grid. Each bin corresponds to a 100km^2 square.
4. **East Japan:** This area corresponds to Japan's north-eastern coast. It includes both inland and off-shore events, which makes it more difficult to forecast. It also includes the location of the M9 earthquake of 2011. We define this region as starting at N37,W140, with 1600 bins arranged in a 40x40 grid. Each bin corresponds to a 100km^2 square.

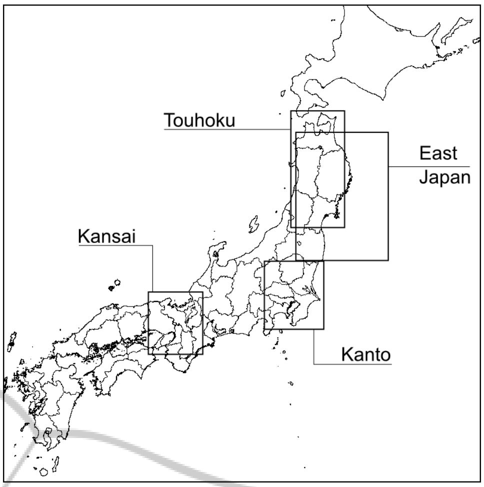


Figure 3: The relative locations of the four areas used in our experiments.

5.2 Experimental Design

To compare the performance of the different forecast models, we execute a simulation experiment on 32 scenarios. A scenario is defined by a target region and a target time interval. The region is selected from the four regions described in the previous section. The time interval is a one year interval, lasting from Jan/01 to Dec/31. We consider 8 periods (from 2005 to 2012). In each period, we use 5 years of prior data (2000 to 2011) to train the RI and GAM algorithms.

For each scenario, we generate forecasts for the random model, the GAM model (using the second fitness function described in this paper) and the RI model. The random forecast is generated by selecting a random uniform value between 0 and 1 for each bin, and transforming this value into an integer using Algorithm 1. The RI forecast is generated according to Section 5.3.

Both the GAModel and the RI algorithm require a training data set. For each scenario, we use earthquake data from the 5 year period immediately prior to the testing period. In order to test the statistical significance of our results, we run the GAModel 20 times, and obtain 20 forecasts. All GAModel results, unless noted otherwise, are the mean of these 20 runs. Because the RI algorithm is not stochastic, the result of a single run is reported.

The results are compared in mainly two ways. We report the log likelihood values for the three methods. The log likelihood indicates how close the forecast

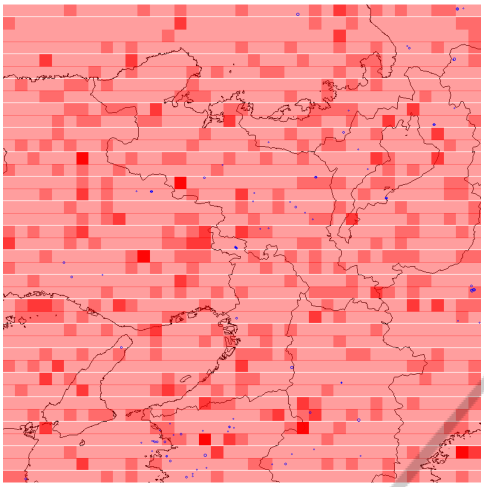


Figure 4: A random forecast (Kansai Region, 2007).

is to the test data, in terms of location and quantity of earthquakes. We also report the Area Skill Score (ASS) for the three methods. The ASS is the area covered by the "Alarm rate x Miss rate" curve of the forecast (see Section 2.2 for details). In both cases, a higher value indicates a more skilled model.

5.3 The Relative Intensity Algorithm

The Relative Intensity (RI) algorithm is a commonly used benchmark for earthquake forecasting models. In this experiment, we use it as goalpost to assess the suitability of evolutionary computation for earthquake forecasting.

The working assumption behind the RI is that larger earthquakes are more likely to occur at locations of high seismicity in the past. Accordingly, the RI algorithm will estimate the number of earthquakes in a bin based on the number of earthquakes observed in the past for that bin. This estimate will be "smoothed" by an attenuation factor s that takes into account the seismicity of neighboring bins.

We use the implementation described by Nanjo in (Nanjo, 2011). Please refer to that paper for implementation details. The parameters used for the RI algorithm in these experiments are: $b = 0.8$ and $s = 50km$. These values were selected by taking the suggested range of values recommended in (Nanjo, 2011), and finding the best values in this range on the same data set used to tune the parameters of the Genetic Algorithm.

5.4 Comparison of Forecast Models

The results of the simulation experiments are summarized in Table 2. In this table, *Random* refers to the Random forecast, *RI* to the Relative Intensity algorithm, and *GA* to the GAModel.

The GA column reports the average for 20 runs, and the standard deviation is reported in parenthesis. The *p-value* column indicates the result of an one-sided T-test of the GA's mean against the value obtained from the RI algorithm.

Looking at the table, we observe that the GAModel has generally outperformed the RI on the "Kanto" area. Figures 5(c) and 5(d) illustrate the reason: Generally, GAModel is able to detect smaller earthquake clusters inland, while RI smooths them out.

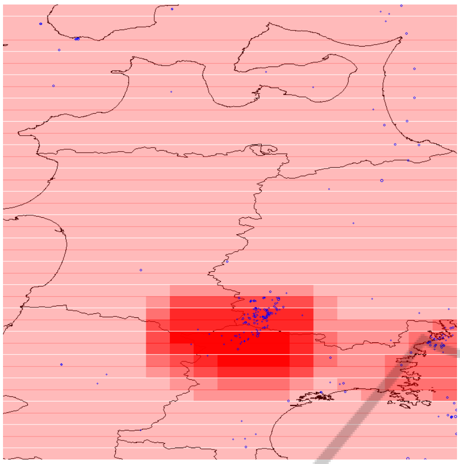
Even then, both models miss some clusters in this area, as indicated by their ASS value being under the value of the random model. The ASS value is useful to estimate how much a forecast is suffering from over fitting - a low value indicates that a larger alarm area is necessary to reduce the miss rate of the forecast.

The "Touhoku" area shows a similar situation as the "Kanto" area. In Figures 5(a) and 5(b) we can see that GAModel is able to identify the two earthquake clusters more precisely, while the RI algorithm casts a wide net which reduces the forecast accuracy. The ASS score for this area is higher. This is because both methods are able to learn the two "hot spots" for seismic activity, unlike the Kanto area where some clusters would appear in different locations along the years.

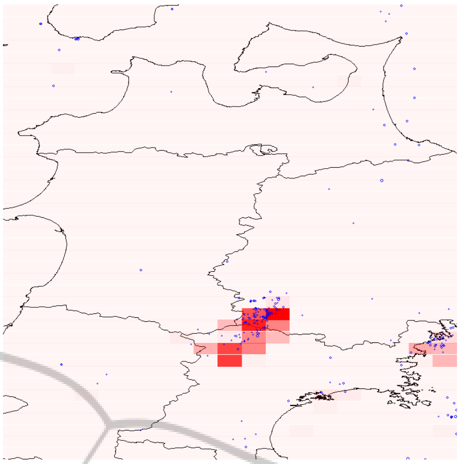
Conversely, in the "East Japan" area the RI algorithm performed better than the GAModel. The reason seems to be that off-shore seismicity, which is spread over a larger area than inland events, is better captured by the wide smoothing step of the RI algorithm.

In all three cases, we can see that the results changed wildly in the aftermath of the 2011 M9 earthquake. That earthquake caused a sudden large spike of seismic activity in all areas (Figure 1), including many areas that never showed any seismic activity during the training period. In the following scenario (2012), both methods try to use this new data to reform their forecasts. Again, GAModel performs better in the "Touhoku/2012" scenario, where most earthquakes are inland. The RI method performs better in the "Kanto/2012" scenario, where most of the new seismicity occurs off-shore (Figures 5(e) and 5(f)).

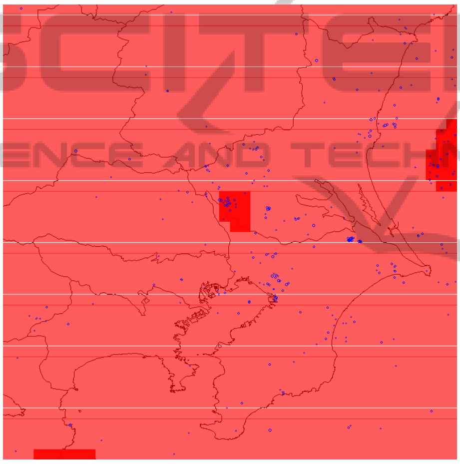
The "Kansai" scenarios turned out to be a special situation for both algorithms. The seismic activity in that area for the period was too sparse. Since both the RI and GAModel depend on the analysis of recent earthquakes, neither algorithm could produce a reliable forecast. In the case of the RI, the forecast



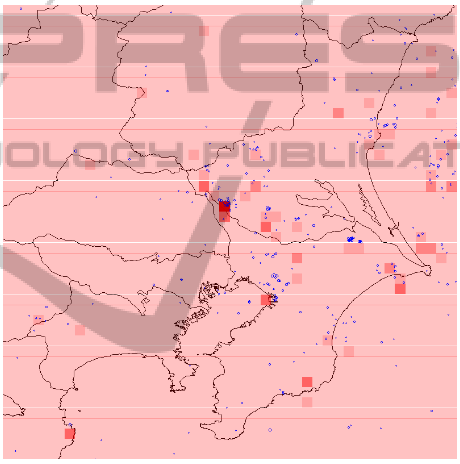
(a) Touhoku 2009, RI forecast



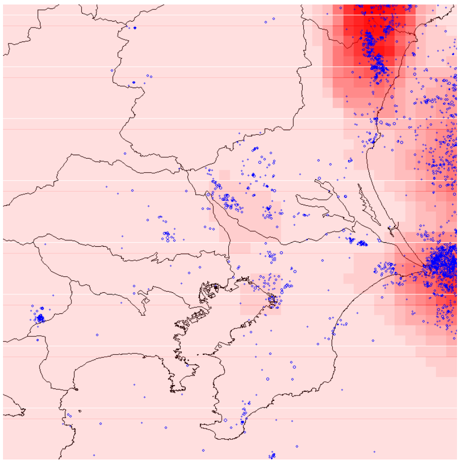
(b) Touhoku 2009, GA forecast



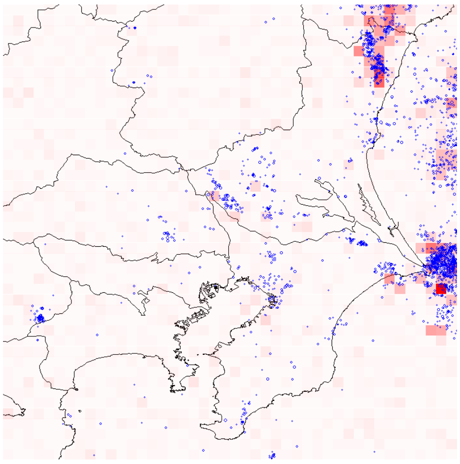
(c) Kanto 2010, RI forecast



(d) Kanto 2010, GA forecast



(e) Kanto 2012, RI forecast



(f) Kanto 2012, GA forecast

Figure 5: Some forecast images for the RI algorithm and the GAModel. Red squares indicate the intensity of the forecast. Blue circles indicate actual earthquakes in the test data. Note that the intensity of the red color indicates relative values in the forecast. In other words, uniform forecasts will tend to appear as a darker red color than forecasts with a bigger range of values.

Table 2: Results from the simulation experiments. The parenthesis after the GA values are the standard deviation (average of 20 runs). The two "p-value" columns report the significance of the t-test comparing the GA mean against the result from the RI algorithm. For the sake of legibility, p-values under 0.01 are reported as 0.01.

Scenario		Log Likelihood				Area Skill Score			
		Random	RI	GA	p-value	Random	RI	GA	p-value
Kanto	2005	-3716.86	-2263.4	-2253.2 (16.5)	0.01	0.38	0.24	0.24 (0.04)	0.78
	2006	-3884.85	-2252.28	-2234.72 (14)	0.01	0.36	0.10	0.18 (0.01)	0.01
	2007	-3838.9	-2113.84	-2108.95 (11.1)	0.03	0.36	0.15	0.19 (0.02)	0.01
	2008	-3914.54	-2110.79	-2096.75 (11.8)	0.01	0.39	0.16	0.22 (0.03)	0.01
	2009	-4211.28	-2487.88	-2482.88 (10.3)	0.02	0.36	0.09	0.14 (0.01)	0.01
	2010	-4010.47	-2132.11	-2099.13 (16.3)	0.01	0.39	0.14	0.28 (0.03)	0.01
	2011	-17657.43	-20083.09	-19983.73 (144.4)	0.01	0.35	0.07	0.08 (0.02)	0.14
	2012	-10863.99	-3225.39	-4435.34 (248)	1.00	0.48	0.80	0.77 (0.01)	1.00
Kansai	2005	-2219.06	-1605	-1631.96 (26)	0.99	0.24	0	0.07 (0.02)	0.01
	2006	-2172.29	-1606	-1631.19 (23.9)	0.99	0.23	0	0.05 (0.01)	0.01
	2007	-2024.77	-1615	-1617.01 (2.3)	0.99	0.22	0	0.03 (0.01)	0.01
	2008	-2038.16	-1608	-1610.41 (1.54)	1.00	0.22	0	0.01 (0.01)	0.01
	2009	-2054.23	-1618	-1619.51 (2.58)	0.99	0.21	0	0.02 (0.01)	0.01
	2010	-2054.63	-1613	-1611.00 (2.27)	0.01	0.27	0	0.07 (0.02)	0.01
	2011	-2059.89	-1625	-1625.12 (2.46)	0.58	0.26	0	0.05 (0.03)	0.01
	2012	-2080.35	-1601	-1603.59 (2.92)	0.99	0.22	0	0.04 (0.02)	0.01
Touhoku	2005	-2552.61	-1067.38	-984.23 (84)	0.01	0.58	0.58	0.62 (0.01)	0.01
	2006	-2613.1	-1044.72	-1073.03 (154)	0.78	0.52	0.50	0.42 (0.03)	1.00
	2007	-2666.11	-1049.82	-999.64 (83.6)	0.01	0.51	0.51	0.41 (0.01)	1.00
	2008	-5124.54	-5007.49	-4704.15 (131)	0.01	0.36	0.05	0.18 (0.01)	0.01
	2009	-2737.47	-1049.22	-936.63 (60)	0.01	0.54	0.67	0.70 (0.01)	0.01
	2010	-2714.68	-1045.03	-1077.95 (136)	0.85	0.53	0.66	0.57 (0.01)	1.00
	2011	-3435.67	-2753.95	-2963.31 (88)	1.00	0.40	0.21	0.10 (0.01)	1.00
	2012	-3623.22	-1326.52	-1186.1 (45.3)	0.01	0.47	0.62	0.70 (0.05)	0.01
East Japan	2005	-2666.11	-1049.82	-868.87 (20)	0.01	0.47	0.35	0.30 (0.02)	1.00
	2006	-6596.76	-2130.69	-2303.78 (98)	1.00	0.46	0.42	0.35 (0.01)	1.00
	2007	-6714.36	-1997.78	-2065.4 (85)	0.99	0.43	0.51	0.34 (0.02)	1.00
	2008	-8784.64	-6087.88	-6097.63 (264)	0.56	0.46	0.23	0.20 (0.03)	1.00
	2009	-6435.07	-2052.35	-1964.72 (106)	0.01	0.47	0.49	0.48 (0.02)	0.99
	2010	-6560.97	-2572.97	-2541.33 (121)	0.12	0.46	0.41	0.31 (0.01)	1.00
	2011	-31447.79	-47704.35	-51485.77 (536)	1.00	0.44	0.40	0.18 (0.01)	1.00
	2012	-19068.86	-5177.55	-6657.52 (478)	1.00	0.50	0.77	0.71 (0.01)	1.00

produced was largely a uniform forecast, where all bins had equal or very close expectation values. In the case of GAModel, A few bins where earthquakes had happened in the training data were marked with higher forecasts, but no consistent activity clusters were identified. The log likelihood or ASS scores for these scenarios cannot really be used to compare the two methods.

6 CONCLUSION

Our goal in this work was to open the discussion about the feasibility of Evolutionary Computation approaches for the important problem of generating earthquake forecast models. The mechanisms of earthquake generation are still not fully understood, which motivates us to use self-adaptive methods such as Genetic Algorithms.

To illustrate our proposal, we designed GAModel, a traditional GA with an specific fitness function that generates an earthquake forecast based on recent seismic history. We performed simulation experiments and compared the results with the RI method, which is accepted in the seismology community as a natural benchmark.

Our results show that the GAModel is competitive with the RI algorithm, outperforming it in scenarios with a predominance of in-land earthquakes, and being outperformed when there is a large number of off-shore earthquakes. In this sense, we feel that the answer to the question posed by the title of the paper should be "Yes, it is promising to use EC to generate earthquake forecasts".

That said, we have also identified many places where an Evolutionary forecast generator could be improved. Although the time-slice fitness function was designed to reduce over fitting, we still see that

GAModel generates "sharp" forecasts that are probably the result of some degree of over fitting.

In this paper, we have decided to focus on the introduction of this new problem domain to the evolutionary computation community. Therefore, we limited ourselves to the traditional GA. However, we visualize many possible research directions based on the shortcomings demonstrated in the current research.

One way to mitigate the sharpness noticed in the results is by making the algorithm aware of data locality. Based on the smoothing pattern in the RI algorithm, we plan to develop a self-adaptive way to smooth the results in the GAM. Also, because in the RELM each bin is ultimately evaluated independently of the neighboring bins, it is feasible to imagine that separate areas in a forecast model could be generated by using different parameters, or different algorithm variations altogether.

Finally, we currently only use historical data to build the forecast model. We are very interested in finding ways to add domain knowledge into the system, such as the location of known faults, in order to improve the forecast ability.

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