A HYBRIDIZED GENETIC ALGORITHM FOR COST ESTIMATION IN BRIDGE MAINTENANCE SYSTEMS

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Keywords: Hybridized Genetic Algorithm, Cost Estimation, Bridge Maintenance Systems.

Abstract: A hybridized genetic algorithm is proposed to determine a repair schedule for a network of bridges. The schedule aims for the lowest overall cost while maintaining each bridge at satisfactory quality conditions. Appreciation, deterioration, and cost models are employed to model real-life behaviour. To reduce the computational time, pre-processing algorithms are used to determine an initial genome that is closer to the optimal solution rather than a randomly generated genome. A post-processing algorithm that locates a local optimal solution from the output of the genetic algorithm is employed for further reduction of computational costs. Experimental work was carried out to demonstrate the effectiveness of the proposed approach in determining the bridge repair schedule. The addition of a pre-processing algorithm improves the results if the simulation period is constrained. If the simulation is run sufficiently long all pre-processing algorithms converge to the same optimal solution. If a pre-processing algorithm is not implemented, however, the simulation period increases significantly. The cost and deterioration tests also indicate that certain pre-processing algorithms are better suited for larger bridge networks. The local search performed on the genetic algorithm output is always seen as a positive add-on to further improve results.

1 INTRODUCTION

There is an increasing need for immediate and long-term infrastructure renewal of provincial and municipal highways and roads, buildings, water supply systems, wastewater treatment facilities, sanitary and storm sewers, and bridges and overpasses. The gross value of these assets amounted to $286.2 billion in 2007. The need of the renewal is caused in part by the large scale boom in infrastructure that occurred 30 to 60 years ago. The average life of these structure ranges from 28.2 years for highways and roads to 43.3 years for bridges and overpasses (CBC News, 2008). As such, governments have the arduous task of budgeting for a backlog of repairs and reconstructing of existing infrastructure. To limit the current budgets, alternative systems are presented to seek the optimal cost per cycle solutions to support the repair or reconstruction of the aging infrastructure.

Once built, bridges receive little maintenance, unlike other infrastructures, such as roads and water infrastructure, which are maintained or repaired periodically. Changing weather conditions and the steady rise in traffic levels have caused existing bridges to depreciate at a much higher rate. According to a 2006 Statistics Canada study, bridges are at 49% of their useful life (Charles Mandel, 2007). Saeed Mirza in (Charles Mandel, 2007) states that the current situation is disastrous and estimates that $100 billion should be invested to upgrade existing bridges and other infrastructure. A 2007 report issued by the Residential and Civil Construction Alliance of Ontario warns that 40% of Ontario's bridges will require significant repair over the next few years (Bruce Campion-Smith, 2007). The catastrophic collapse of the I-35 Bridge in Minneapolis, Minnesota on August 2, 2007 has increased public awareness of the importance of maintaining bridges. Clearly there is an increasing need to invest in bridge infrastructure.

Shaban K., Younes A., Good N., Iqbal M. and Lourenco R. (2010).
A HYBRIDIZED GENETIC ALGORITHM FOR COST ESTIMATION IN BRIDGE MAINTENANCE SYSTEMS.
In *Proceedings of the 12th International Conference on Enterprise Information Systems - Artificial Intelligence and Decision Support Systems*, pages 428-433
DOI: 10.5220/0002974304280433

Traditionally, in bridge maintenance systems (BMSs), experts use their judgment and experience to determine which bridges to repair and the extent of repair each year. However, as the number of bridges increases, this task evolved into a complex optimization problem that is well beyond the abilities of even the most experienced experts. In fact, this problem is a nondeterministic polynomial (NP) problem, which is computationally intractable for traditional methods. Genetic Algorithms (GAs) have been shown to be effective in solving NP-hard problems, and thus are good candidates for solving this problem.

The bridge inventory contains a list of all the bridges in the network. Each bridge component has a condition rating. The deterioration and improvement models quantify how much the bridge components degrades or improves its condition each year, depending upon whether a repair takes place or not. The cost model determines how much a repair will cost. This model depends on the current condition rating of the bridge. All models occur over a predetermined time period. The evolutionary algorithms try to optimize (minimize) the total cost spent over the time period. The total cost is optimized by determining which bridges to repair and which components on the bridge to repair.

2 A HYBRIDIZED GA FOR COST ESTIMATION IN A BMS

The GA derives a solution based on a fitness function and constraints. Parameters such as mutation rate, the number of generations and crossover rate are also to be tuned. The fitness function is to minimize the overall repair cost for the bridge network over the desired time period. The overall repair cost is calculated by summing the costs for each year. The other option was to make the fitness function based on the quality of the bridges. However, due to safety considerations, the bridge quality was deemed better suited as a hard constraint. Several constraints were added to the implemented system including:

1. Repairs Constraint:

A bridge can only be repaired maximum of two times over a 5 year period, or 5 times over a 20 year period. This constraint reflects real life constraints. Bridges that are repaired constantly incur higher costs (both construction costs and user costs).

2. Condition Constraint:

The condition of a bridge cannot fall below 30. Furthermore, a bridge cannot be repaired if its condition exceeds 90. These conditions maintain a satisfactory bridge quality level and eliminate the possibility of repairing well-conditioned bridges.

3. Cost Constraint:

A predefined yearly budget is be defined. The yearly budget is related to the number of bridges within the system. This constraint reflects real life budget restraints.

In order to reduce the time to develop an acceptable solution, some pre-processing of the data must take place. The initial data set that the GA uses to optimize the fitness function should be conditioned to be within the ball park of the final solution. For example, we know that in any given year, because of budgetary limits, only several bridges are repaired. Therefore, the GA chromosome (i.e. bridges to repair) will initially be setup to repair only a small percentage of the bridges per year. In order to determine these initial values, we will use fuzzy sets, among other approaches (to be investigated). The fuzzy set outputs will be no repair, light repair, medium repair and extensive repair. They will correspond to the condition of the bridge – the input fuzzy sets.

A post-processing algorithm can be used to locate a local optimal solution. Genetic algorithms are capable of determining the optimal solution. However, even with the inclusion of pre-processing, determining the optimal solution may take a substantial amount of time. The post-processing algorithm can determine a better solution by slightly altering the bridge repair schedule (represented as the genome). For example, if a heavy repair is made in year X for a bridge, the post-processing algorithm can determine if a local optimal solution is found by downgrading the repair severity to a medium or light repair, or altering the time or repair to year X+1 or year X−1. The post-processing algorithm can also be used to check the output from the genetic algorithm. An emphasis is made to limit the computations required for the post-processing algorithm.

2.1 Pre-processing

The motivation behind pre-processing the genome is to reduce the computational time required to produce the optimal solution. Four pre-processing algorithms were implemented.

The first algorithm randomly generates genome. For any bridge/year combination, it has a 5% chance of assigning a level 1 repair, a 3% chance of assigning a level two repair, a 2% chance of assigning a level three repair, and a 90% chance of assigning no repair at all.

The second algorithm repairs 10% of the bridges every year. If the bridge's quality is below 35 it assigns a level 3 repair. If the quality is between 35 and 50, it assigns a level 2 repair. If the quality is above 50, it assigns a level 1 repair. After assigning the repairs for each year, it recalculates the bridge qualities for the subsequent years.

The third algorithm will repair any number of bridges. If the bridge's quality falls below 40, it will be repaired. Given a five year study if this occurs in the first year, a level 3 repair will be assigned. If the quality falls below 40 in the second or third year, a level 2 repair will be assigned. If it falls below 40 in the fourth or fifth year, a level 1 repair will be assigned.

The fourth algorithm repairs a set number of bridges each year. Given a five year study, three bridges are repaired each year. It applies a level 2 repair to the worst bridge and level 1 repairs to the other two bridges. It will not repair a bridge unless it is below a quality of 50 and will not repair the same bridge twice.

2.2 Post-processing

It was noticed during the testing that even with a relatively small study size, the genetic algorithm took a very long time to converge to the optimal solution (6-7 hours). In order to combat this, a post-processing algorithm was implemented. In these cases, the post-processing algorithm can be run on any results the GA produced before it was stopped to improve upon those results.

The post-processing algorithm looks at each repair that is being made, and examines the effect of lowering it one level (e.g. level 3 repair to level 2, or level 1 to no repair). If lowering the repair level does not cause any bridge to fall below the quality threshold of 30, it will be lowered. Otherwise it will be kept at the same level. This is a local search that is used to refine the genetic algorithm results.

2.3 Appreciation Model

After a repair, the quality of the bridge will increase. The amount of increase is dependent on the severity of the repair. There are three levels of repair in the proposed system: light repair, medium repair, and heavy repair. Light repair is used to recondition the bridge elements; this includes but is not limited to resurfacing the deck. Medium repair is used to replace elements within the bridge. Elements can include joints within the bridge structure. Heavy repair is used to replace most of the bridge.

Given the limited information on the deterioration of the bridges, all three types of repair will produce a static improvement in the bridge quality. For example, if a light repair is used on bridge A, the quality of bridge A will increase by ten points. A medium repair will result in an increase of 30 points. Heavy repair results in an increase of 50 points. All three types of repair are independent of the age and existing condition of the bridge. The maximum bridge quality after any repair is 90.

The formula used to calculate the condition of a bridge after a repair is made is shown below and Table 1 lists the i_C and I constants for each repair level.

$$C = P(1 + i_C) + I \tag{1}$$

where:

C = bridge condition

P = previous bridge condition

i_C = condition improvement percentage

I = bridge improvement

Table 1: Appreciation Model Constants.

Repair Level	**i_C**	**I**
Light	15%	10
Medium	20%	30
Heavy	30%	50

2.4 Deterioration Model

The deterioration of the bridge is the process of decline from its original condition under normal operating circumstances (Abed-Al-Rahim, I. and Johnston, W., 1995). This process excludes rare phenomena such as natural disasters and includes physical and chemical changes (Hatem Elbehairy, 2007) (Yang, Ming-Wing, 2007). Examples of each include general wear to components of the bridge like the deck and the bridge's joints, and rusting on bridge members.

Common factors which affect the rate at which a bridge will deteriorate include the bridge's age, the average traffic levels, exposed environment conditions, the design of the bridge, and the quality of the material used to construct the bridge. The only available information for this study is the bridge's age, its current depreciation, and it's expected remaining lifespan. As such, the depreciation model will only reflect these parameters.

For this study a mechanistic deterioration model (Hatem Elbehairy, 2007) will be employed. A mechanistic model employs a known nonlinear relationship in the form of Equation 2. The mechanistic deterioration model is simple to implement and computationally inexpensive. The values of A and B can be assigned or determined using fuzzy inference. The mechanistic model reflects changing deterioration per year, where the deterioration rate decreases as the bridge gets older.

$$C(t) = Ae^{-Bt} \tag{2}$$

Since the deterioration of the bridge is the process of decline from its original condition under normal operating circumstances, a simple decaying exponential was used to approximate the deterioration. In the formula used to calculate deterioration shown in equation (2), the deterioration is related to deterioration rate provided in the original data. The inclusion of the deterioration rate reflects the different rate of decay for each bridge. The multiplier is a constant for each bridge. The multiplier was modified until it conformed to a deterioration rate found in various literature sources on the subject.

The deterioration and appreciation models were combined to produce a single model which updates the condition of the bridges on a yearly basis.

$$C = Pe^{\frac{-1}{dm}} \tag{3}$$

where:
C = bridge condition
P = previous bridge condition
d = deterioration rate
m = multiplier

2.5 Cost Model

The cost model is used to determine the costs associated with repairing a bridge within the network of bridges. Generally there are two cost models associated with a BMS: the user cost model and the repair cost model. The cost model used in our approach will only look at repair costs. User costs are extra costs which are paid by the bridge user (i.e. financial cost of time spent in traffic). User costs are omitted from our approach because they are generally subjective.

Table 2: Repair Unit Costs.

	Rehabilitation Category	Unit Cost ($/ft²)
1	Deck Overlay	$32.28
2	Deck Widening	$69.48
3	Deck Replacement and Widening	$72.70
4	Major Reconstruction	$27.57
5	Deck Replacement	$30.19
6	Superstructure Replacement	$35.23

The repair costs can be expressed either as a unit cost or a percentage of the initial cost of the bridge. Unit costs are associated with the costs of repairing individual items of the bridge (Saito, M., and Sinha, K., 1990). An example of user costs is shown in Table 2. Our approach will determine the cost of repair as a percentage of the initial cost. This approach is less computational. Furthermore the limited information provided for each bridge makes the unit cost approach impossible to implement.

The formula to calculate the cost of a repair is based on the initial construction cost of the bridge, which was provided. The formula for the repair cost is shown below and Table 3 lists the multiplier constants for each repair level.

$$RC = CM \tag{4}$$

where:
RC = repair cost
C = construction cost (specified for each bridge)
M = repair type multiplier

Table 3: Cost Model Constants.

Repair Level	M
Light	0.1
Medium	0.4
Heavy	0.6

3 EVALUATION

Testing is focused on finding the best pre-processing algorithm. The first step was to establish a set of testing conditions which would allow us to properly compare the different algorithms. We then changed the testing conditions to observe the effect on the optimal solutions.

To keep our testing consistent, we needed to fix the number of bridges (study sample size) and the number of years (study period). Although we had data for 161 bridges, and could extrapolate the bridge quality for any number of years using the deterioration and appreciation models, we elected to use a sample of 20 bridges over a 5 year period. The crossover and mutation rate used for the genetic algorithm was set at 0.5 and 0.1 respectively.

As mentioned, the main testing parameter will be the pre-processing type. In addition to testing the effectiveness of each pre-processing type, additional tests will be conducted to determine the effects of changing the deterioration rate and costs.

3.1 Pre-processing Algorithms Comparison

Although we created four pre-processing algorithms, the first one, which was random, either failed to find valid solutions or took a very long time to do so in our testing. As a result, we concluded that this was not a suitable method for pre-processing (as expected) and focussed our attention on the remaining three algorithms.

In order to compare the effectiveness of the three remaining pre-processing algorithms, tests were run that involved setting all the variables in the system constant while only changing the pre-processing the algorithm. Table 4 shows the systems settings for the initial comparison.

Table 4: Initial Pre-Processing Comparison Settings.

System Constants	
Stop Condition	8500 Trials
Population Size	**200**
Bridges	20
Years	**5**
Repairs/Bridge	3
Yearly Budget	**$6,500,000**
Minimum Bridge Quality	30
Maximum Bridge Quality	**90**

Looking at the above table we see that the tests were run for 8500 trials, which is a relatively short period of time but sufficient enough to show a system trend. Table 5 shows the results obtained from running the tests with each pre-processing algorithm over 5 runs.

Table 5: Initial Pre-Processing Results.

Average Test Results After 5 Runs

	Starting Total Cost	End Total Cost	% Valid Trials
Pre-processing 2	$17,200,000	$14,700,000	68
Pre-processing 4	**$13,400,000**	**$12,000,000**	**74**
Pre-processing 3	$14,000,000	$12,500,000	74

We can see that pre-processing algorithm 2 starts in a state with the lowest total cost, among the three, and finishes with the lowest total cost. Similarly, the first pre-processing algorithm has the highest staring and end total cost. This indicates that, with all variables set, the quality of the starting state dictates how good the end state will be, in a given amount of time.

Table 6: Optimized Pre-Processing Constants.

System Constants	
Stop Condition	30 minutes
Population Size	**50**
Bridges	20
Years	**5**
Repairs/Bridge	2
Yearly Budget	**$2,000,000**
Minimum Bridge Quality	30
Maximum Bridge Quality	**90**

Of course, over a long enough time period all solutions will converge to a global optimum, but our concern is to determine which method will do this the quickest or which method will produce the best result in a given time frame.

To confirm that all methods will converge to an optimum the tests were run for much longer. The new systems constants are shown in Table 6.

The stop condition was changed from 8500 trials to 30 minutes. The population size was reduced to 50 to reduce the consumption of computer memory. The bridge repairs per year and yearly budget constraints were reduced to find a solution with fewer repairs. The random pre-processing algorithm was also included. The test results are summarized in Table 7.

Table 7: Optimized Pre-Processing Results.

	Starting Total Cost	End Total Cost	Number of Repairs
Pre-processing 1	**$8,615,700**	**$299,400**	**5**
Pre-processing 2	$3,873,200	$262,600	4
Pre-processing 3	**$5,104,700**	**$228,500**	**4**
Pre-processing 4	$3,889,500	$224,100	4

The total cost converges to around $200,000 for all of the pre-processing algorithms. This clearly shows that there is a global optimum that is eventually reached.

3.2 Other Parameter Testing

Changes to the cost and the deterioration models were made to evaluate the effects on the optimal solution determined in section 2.2. The random pre-processing method was omitted from both tests.

The first test was to determine the effect of changing the cost model. The repair type multiplier for light repairs was changed to 0.2. Table 8 displays the system constants used for the test. The test results are shown in Table 9.

Table 8: Test Constants for Cost Model Testing.

System Constants	
Stop Condition	30 minutes
Population Size	**50**
Bridges	20
Years	**5**
Repairs/Bridge	2
Yearly Budget	**$2,000,000**
Minimum Bridge Quality	30
Maximum Bridge Quality	**90**

The second test was to determine the effect of changing the deterioration model. The deterioration multiplier was changed from 10 to 5. Table 10 displays the system constants used for the test. The test results are shown in Table 11.

Table 9: Test Results for Cost Model Test.

	End Total Cost	Number of Repairs
Pre-processing 2	$546,200	6
Pre-processing 3	**$354,600**	**3**
Pre-processing 4	$468,200	5

Table 10: Test Constants for Deterioration Model Testing.

System Constants	
Stop Condition	30 minutes
Population Size	**50**
Bridges	20
Years	**5**
Repairs/Bridge	2
Yearly Budget	**$4,000,000**
Minimum Bridge Quality	30
Maximum Bridge Quality	**90**

Table 11: Test Results for Deterioration Model Test.

	End Total Cost	Number of Repairs
Pre-processing 2	$1,517,100	9
Pre-processing 3	**$1,544,000**	**10**
Pre-processing 4	$1,610,200	10

As expected, the optimized total costs increased for both tests. A more profound discovery is that the pre-processing 2 algorithm outperformed the other two algorithms for the deterioration model test. By increasing the multiplier, the deterioration per year increased significantly. As a result more bridges required repair. Pre-processing algorithm 2 is better equipped at handling larger bridge repair demands since it is capable of repairing a constant number of bridges per year. Pre-processing algorithms 3 and 4 will only repair the lowest quality bridges. If there is a large number of bridges that fit this criterion in a single year the algorithm may have difficulties addressing all the bridges.

3.3 Post Processing Results

To demonstrate the effectiveness of the post-processing algorithm, it was applied to the three simulations for the network of 20 bridges over a five year study term. The cost improved from $224,000 to $7,800.

4 CONCLUSIONS

Experimental tests showed that when a pre-processing algorithm was applied prior to the genetic algorithm, the genetic algorithm was able to obtain a better solution in a fixed period of time than when no pre-processing took place. More specifically, pre-processing algorithms 3 and 4 generally resulted in the best performance. However, when the deterioration model was modified to increase the rate of bridge deterioration, pre-processing algorithm 2 was the top performer. This shows that pre-processing algorithm two is the most flexible of those tested. This is important, as different municipalities or government may have very different models for appreciation, depreciation and repair cost. Pre-processing algorithm 2 is best equipped to deal with these variations as the number of bridges repaired is not static (as is the case in pre-processing algorithms 3 and 4).

A post-processing algorithm was devised to improve upon the genetic algorithm solution. While the algorithm was implemented and preliminary tests showed that it was successful in improving upon the solution obtained by the genetic algorithm, more testing is required with a wider range of conditions to confirm that the post-processing algorithm is effective.

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