Journal of Engineering and Applied Sciences 11 (7): 1682-1686, 2016
ISSN: 1816-949X


# Evaluation of Hybrid Monte-Carlo and Genetic Algorithm for Tropical Timber Joint Strength

[1, 2]Marina Yusoff, [2]Dzul Fazwan Othman,[2]Amirul Thaqif Latiman and [3]Rohana Hassan
[1]Institute for Infrastructure Engineering and Sustainable Management (IIESM),
[2]Faculty of Computer and Mathematical Sciences, [3]Faculty of Civil Engineering,
Universiti Teknologi MARA, 40450 Shah Alam, Selangor, Malaysia

**Abstract:** The timber strength is one of the prime important aspects of timber structure design. A lot of laboratory experiments have been conducted to determine an appropriate load for timber strength. This paper addresses a new design of a hybrid genetic algorithm-Monte Carlo for load prediction in timber joint. A hybrid of Genetic Algorithm Monte-Carlo is employed to determine the best load value for the prediction of timber joint strength. This study discusses the initial solution to overcome the time consuming and costly incurred of the laboratory experiments. A new solution representation of Genetic Algorithm was addressed with the introduction of Monte-Carlo calculation. Two types of tropical timbers which are Keruing and Sesenduk are used. The results demonstrate faster solution due to fast convergence of obtaining a feasible solution. At the same time the hybrid solution also gives a sub-optimal solution. However, more computational experiments are expected to be done for various types of timbers. The comparison with other computational methods and different parameters should be considered to find better solutions.

**Key words:** Genetic algorithm, hybrid genetic algorithm Monte-Carlo, tensile test, timber joint, tropical timber

## INTRODUCTION

The use of timber has become very popular for building and housing constructions and it is widely used until now. Timber is proven given benefits to construction industries as it has the capability in its strength (Hassan *et al*., 2014). However, the structural evaluation of existing timber structures presents a challenge due to the necessity to assess the mechanical behavior of joints (Feio and Machado, 2015). Thus, the determination of timber joint strength is critical mainly in designing the roof truss (Buchanan *et al*., 2015; Baharudin *et al*., 2015). To know the strength of timber joint, many laboratory tests such as tensile test, bending stress test and compression test are used. Such test requires a lot of laboratory experiments to determine the strength of timber joint (Yusoff *et al*., 2014). It incurred high cost and consumed a lot of time (Yusoff *et al*., 2014; Hassan *et al*., 2014). Tropical timbers are normally harder than Europe timber. This means the strength of tropical timber and Europe are different (Puaad *et al*., 2014). There is still a lack of study to determine the strength of tropical timber, although tropical timber has its own standard based on the support group. Eurocode that was established in Europe is shown not appropriate to tropical timber due to tropical timber has its own characteristics. Lack of general information seems to be an obstacle in developing more appropriate joint in timber construction industries.

Sawata *et al*. (2000) focused on the calculation of the strength of bolted timber joint and the predictive strength of bolted joint using Monte-Carlo simulation. In this case, Japanese Industrial Standard SS400 was used as references. Monte-Carlo simulation was enhanced from the deterministic method to probabilistic design method. The probabilistic design method uses the probabilistic value of the load and the strength material to design the building with several processes to calculate the strength of bolted timber joint. Yasumura *et al*. (2012) used probabilistic technique to determine the yield mode of dowel type joint and the relation between the member thickness and yield mode to dowel diameter and Monte-Carlo simulation is responsible to calculate the failure mode of the joint subjected to the force perpendicular to the wood grain. This simulation shows that the deterministic approach gives fairly good prediction of the yield mode of dowel-type joints.

Some research employed evolutionary algorithms demonstrated some feasible solutions in determining the failure mode based on the type of timber. Particle Swarm Optimization (PSO) (Hassan *et al*., 2014) and Monte-Carlo

**Corresponding Author:** Marina Yusoff, Institute for Infrastructure Engineering and Sustainabl Managemen (IIESM), Universiti Teknologi MARA, 40450 Shah Alam, Selangor, Malaysia

method (Brites *et al*., 2013; Kirkegaard *et al*., 2011) are some of computational algorithms and statistical methods had applied to various types of timber joints. The use of PSO to simulate a laboratory experiment on tropical timber joints can assist the traditional experimental analysis with suggestion of end distance value for a single shear timber joint. The valuable findings obtained by the implementation of evolutionary algorithms can assist civil engineers, researchers and related parties in finding the timber strength efficiently.

## MATERIALS AND METHODS

**Monte-Carlo simulation:** Monte-Carlo concept was used for the first time right after World War II, it was used to study nuclear fusion. The term Monte-Carlo simulation was given by mathematician Stanislaw Ulam, who loves gambling at the Monte-Carlo casino. Monte-Carlo simulation is a statistical technique used to develop probabilistic system and establish the odds for a variety output (Hammersley, 2013). Monte-Carlo simulation is basically used to randomize numerical experiments to evaluate a mathematical problem and most of the Monte-Carlo simulation is related to real scenarios.

Raychaudhuri (2008) had reported that Monte-Carlo is a statistical distribution is identifying which use as the source for each of the input parameters . The value of the input variable is represented by draw random samples from each distribution. Each set of the input variable will get a set of output variable. The value of every output variable can be one particular end result scenario in the simulation run.

Monte-Carlo simulation is a type of simulation that use a repeated random value and statistical analysis to compare with the result, in other word Monte-Carlo simulation can be considered as what-if analysis (Raychaudhuri, 2008). The advantage of using Monte-Carlo simulation is it does not need specific information about the form of the solution and it's easy to implement on a computer. However, the disadvantage of using Monte-Carlo simulation is hard to estimating error because Monte-Carlo simulation method that is use non-random numerical method may avoid these deficiencies or not be as several impacted (Cheng, 2013). It is hard to calculate the best and worst case scenarios or every input variable and because of that it's hard to make a decision making (Raychaudhury, 2008). In addition, Monte-Carlo is also applied to timber structures for evaluation (Kirkegaard *et al*., 2011). Monte-Carlo simulation and reliability based analysis conducted to determine the failure mode of the subject to the force perpendicular to the timber (Yasumura *et al*., 2012).

**Genetic algorithm:** Genetic Algorithm is one of the popular evolutionary algorithms. It is a search procedure based on the mechanics, natural selection genetics. Genetic Algorithm is parallel, direct and stochastic for global search and optimization which imitates the evolution of the living things. The Genetic Algorithm is a versatile technique which can be applied as global optimization because it is easier to implement for non-differentiable function and discrete search space (Rangel *et al*., 2005).

GA was introduced by John Holland in the 1970s (Eberhart and Shi, 2007). It is a population-based algorithm classified as an evolutionary computation algorithm. GA is biologically inspired from the genetic evolution that performs selection, crossover and mutation of chromosomes. The following is the procedure of a Genetic Algorithm.

**Genetic Algorithm:**
```
1:  Begin
2:  Initialize number of chromosomes
3:  Generate initial solution
4:  Evaluate the fitness of each chromosome
5:  Selection of the fittest chromosomes
6:  Do
7:  Perform crossover for both of the fittest    chromosomes
8:  Create two new offspring
9:  Evaluate the fitness of the new offsprings
10: Select new offsprings
11: While (stopping condition is reached)
12: End
```

The algorithm starts with the initialization of a random population of chromosomes. Step 3 generates an initial solution. Step 4 performs the evaluation of fitness for each chromosome. Step 5 performs a selection of new offsprings can be done based on roulette wheel selection procedure. Step 6 until step 11 is iterated until the stopping criteria is reached.

**Design of hybrid Monte-Carlo and genetic algorithm:**
**Representation:** Chromosome representation has to be established prior to the application of genetic algorithm. Figure 1 shows the chromosome representation with the adaptation of Monte-Carlo calculation. Monte-Carlo calculation is used to generate a random number as a gene's value in a chromosome. Mean and standard deviation were used in next Gaussian method, to generate random numbers based on normal distribution. Mean and standard deviation were initially obtained from laboratory data. Figure 2 demonstrates the process flow of a hybrid Genetic Algorithm and Monte-Carlo. Figure 2 shows all steps from the beginning, starting from the design chromosome representation until result satisfaction or termination criteria are met. The figure shows the

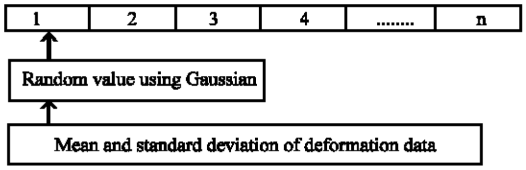


Fig. 1: Chromosome representation

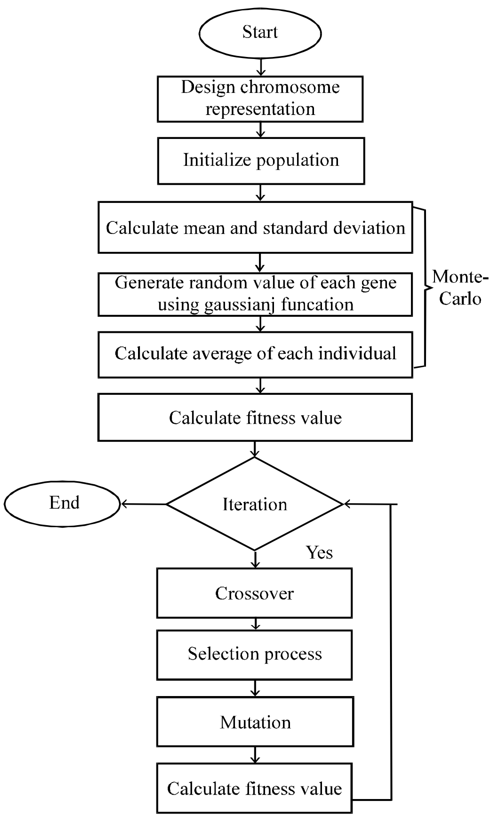


Fig. 2: Process flow of a hybrid Monte-Carlo and Genetic Algorithm

embedding process of Monte-Carlo which considers the calculation of mean and standard deviation, random value generation and average. The process is then followed by fitness calculation, selection process, crossover and mutation.

## RESULT AND DISCUSSION

**Parameter setup:** This system has been tested based on load and deformation of two types of tropical timber; Keruing and Sesenduk to predict the timber strength. Table 1 demonstrates the result obtained from the laboratory experiment for both of the timbers. This load and deformation value is determined based the best strength of the timbers.

Table 1: The best result obtained from laboratory experiments

| Timber | Load | Deformation |
|---|---|---|
| Keruing (Support group 5) | 24.03 | 14.98 |
| Sesenduk (Support group 7) | 11.17 | 19.86 |

Table 2: Parameter setting for a hybrid Genetic Algorithm and Monte-Carlo of Keruing and Sesenduk strength

| Parameter | Keruing | Sesenduk |
|---|---|---|
| Population size | 10, 20, 30 | |
| Iteration | 10, 15, 20, 25, 30 | |
| Probability of mutation | 0.05 | |
| Crossover rate | 0.7 | |
| Mean | 16.6177 | 9.8653 |
| Standard deviation | 5.5067 | 4.1805 |

To value of the mean and standard deviation are used to generate random number by using normal distribution method. Mean and standard deviation for each sample of data is obtained from the data sets from the laboratory experiments. The fitness equation that is used for Genetic Algorithm implementation are based on load over deformation of Keruing and Sesenduk. Equation 1 and 2 show the fitness equation for Keruing meanwhile Eq. 3 and 4 show the fitness for Sesenduk. The average is obtained from each chromosome which is calculated using Monte-Carlo and y is the maximum load:

$$z = (\text{Average} - 9.3)/5.1 \tag{1}$$

$$y = (-9.5\times z^8) + (-22\times z^7) + (16\times z^6) + (55\times z^5) + (-1.6\times z^4) + (-37\times z^3) + (-7.9\times z^2) + (15\times z) + 22 \tag{2}$$

Equation 3 and 4 shows the fitness equation for Sesenduk. Where average is getting from each chromosome and y is the maximum load:

$$z = (\text{Average} - 11)/4.5 \tag{3}$$

$$y = (0.36\times z^7) + (-0.0089\times z^6) + (0.96\times z^5) + (3.1\times z^4) + (3.9\times z^2) + (0.95\times z) + 9.9 \tag{4}$$

The GA and Monte-Carlo technique have a parameter such as population size, number of iterations, probability of mutation, the probability of crossover, mean and standard deviation. Table 2 shows how parameter for Hybrid Genetic Algorithm and Monte-Carlo are being set for the testing process for keruing timber. Table 2 shows the parameter setting for computational experiment of a hybrid Genetic Algorithm and Monte-Carlo.

**Performance of a hybrid genetic algorithm and Monte-Carlo for keruing strength:** Population size of 10 is set and generated for five times as shown in Table 2. The results show that there is a different fitness value were generated. For the fourth running with the iteration of 15, gives the best fitness value for Keruing.

Table 3: Computational results for 10 populations

| Number of runs | Population size | Iteration | Fitness value |
|---|---|---|---|
| 1 | 10 | 10 | 22.03 |
| 2 | 10 | 15 | 21.72 |
| 3 | 10 | 20 | 21.36 |
| 4 | 10 | 25 | 23.49 |
| 5 | 10 | 30 | 22.66 |

Table 4: Computational results for 20 populations

| Number of runs | Population size | Iteration | Fitness value |
|---|---|---|---|
| 1 | 20 | 10 | 21.70 |
| 2 | 20 | 15 | 24.41 |
| 3 | 20 | 20 | 23.31 |
| 4 | 20 | 25 | 22.24 |
| 5 | 20 | 30 | 24.07 |

Table 5: Computational results for 30 populations

| Number of runs | Population size | Iteration | Fitness value |
|---|---|---|---|
| 1 | 30 | 10 | 24.29 |
| 2 | 30 | 15 | 24.04 |
| 3 | 30 | 20 | 23.42 |
| 4 | 30 | 25 | 24.79 |
| 5 | 30 | 30 | 24.52 |

Table 6: Computational results for 10 populations

| Number of runs | Population size | Iteration | Fitness value |
|---|---|---|---|
| 1 | 10 | 10 | 10.79 |
| 2 | 10 | 15 | 10.69 |
| 3 | 10 | 20 | 10.77 |
| 4 | 10 | 25 | 10.81 |
| 5 | 10 | 30 | 10.75 |

Table 3 shows the result of the population 20. It is clearly shown that number of run 5 with 30 iterations provides approximate result which is almost similar to the best fit for the joint strength of Keruing. The load value of 24.07 is obtained where the previous laboratory experiment had recorded 24.03 as shown in Table 1.

Table 4 shows a better fitness value for the load which is 24.04 during the 2nd run with the iteration 15. However, from the table in general, with 30 populations the fitness value is close to 24.03 except the number of run 3 at the iteration 20 which is only obtained 23.42.

From results demonstrated in Table 2-4 it clearly shows the effect of random value generated from the Monte-Carlo calculation. The number of populations used gives different more possibility of having for this testing

the value of iteration has been changed from 10-30. The changes of the iteration give a different result for the best fitness.

**Performance of hybrid Genetic Algorithm and Monte-Carlo for Sesenduk strength:** Table 5 shows the

Table 7: Computational results for 20 populations

| Number of runs | Population size | Iteration | Fitness value |
|---|---|---|---|
| 1 | 20 | 10 | 10.69 |
| 2 | 20 | 15 | 10.90 |
| 3 | 20 | 20 | 10.90 |
| 4 | 20 | 25 | 10.62 |
| 5 | 20 | 30 | 10.81 |

Table 8: Computational results for 30 populations

| Number of runs | Population size | Iteration | Best fitness |
|---|---|---|---|
| 1 | 30 | 10 | 10.86 |
| 2 | 30 | 15 | 10.76 |
| 3 | 30 | 20 | 10.73 |
| 4 | 30 | 25 | 10.84 |
| 5 | 30 | 30 | 10.65 |

computational result for 10 population size. From this table it shows that the different number of iterations gives a different result in the best fitness value. Table 6 shows the result of the population 20, for this testing the value of iteration has been changed from 10 to 30. This change is due to get an accurate result. Table 7 and 8 shows the result of the population 30, for this testing the value of iteration has been changed from 10-30. The changes of the iteration give a different result for the best fitness. From the testing it shows a different result and every population gives different results but a few results are nearly accurate with the laboratory result. The value with the highlight is the value that is almost same with the real experiment.

The introduction of hybrid Genetic Algorithm Monte-Carlo establishes the initialization of random value of load and deformation and yields a limitation in a search space for each chromosome. To obtain an optimal solution (fitness based on load value), the generated population must be able to accommodate the load and deformation of timber strength.

As illustrated in the above results, it can be seen that hybrid Genetic Algorithm Monte-Carlo has capable of converging when using 10 populations. Many feasible solutions are achieved. The adoption of Monte-Carlo calculation in this algorithm has offered faster solution. The good performance in fitness value offered by hybrid Genetic Algorithm Monte-Carlo support the idea that the average and standard deviation used in a random Monte-Carlo calculation contributes to the fast convergence and obtained sub-optimal result. For instance with the use of 30 population size, the fitness of Keruing strength is approximate value when compare to the best result obtained by laboratory experiment. In addition, the role of crossover and mutation rate used are also indirectly support the good results.

## CONCLUSION

This study discusses the initial solution to overcome the time consuming and cost incurred of the laboratory experiments. The use of computational method is introduced, namely hybrid Genetic Algorithm and Monte-Carlo. This algorithm is used to predict the best load of timber joint focusing on tensile strength prediction. A new solution representation of Genetic Algorithm was addressed. The results demonstrate faster solution due to fast convergence for a feasible solution. At the same time the hybrid solution also gives a sub-optimal solution. However, more computational experiments are expected to be done for various types of timbers. The comparison with other computational methods and different parameters should be considered to find better solutions.

## ACKNOWLEDGEMENTS

The researches would like to thank the Faculty of Computer and Mathematical Sciences, Faculty of Civil Engineering, University Teknologi MARA and Institute for Infrastructure Engineering and Sustainable Management (IIESM) in establishing this research.

## REFERENCES

Baharudin, K.S., Z. Ahmad, A. Ibrahim and M. Rassam, 2015. Analysis of Pre-Fabricated Timber Roof Truss. In: InCIEC 2014, Rohana, H., M. Yusoff, A. Alisibramulisi, N.M. Amin and Z. Ismail (Eds.). Springer, Singapore, Asia, ISBN:978-981-287-289-0, pp: 1095-1105.

Brites, R.D., L.C. Neves, J.S. Machado, P.B. Lourenco and H.S. Sousa, 2013. Reliability analysis of a timber truss system subjected to decay. Eng. Struct., 46: 184-192.

Buchanan, A., S. Pampanin and A. Palermo, 2015. U.S. Patent No. 8,935,892. Patent and Trademark Office, Washington, USA.

Cheng, R., 2013. Supporting time-critical decision making with real time simulations. Proceeding of the 2013 Conference on Winter Simulations Conference (WSC), December 8-11, 2013, IEEE, Southampton, England, ISBN:978-1-4799-3950-3, pp: 229-240.

Eberhart, R. and Y. Shi, 2007. Computational Intelligence: Concepts to Implementations. 1st Edn., Morgan Kaufmann, Burlington, USA., ISBN-13: 978-1558607590, pp: 496.

Feio, A. and J.S. Machado, 2015. In-situ assessment of timber structural members: Combining information from visual strength grading and NDT-SDT methods-A review. Constr. Build. Mater., 101: 1157-1165.

Hammersley, J., 2013. Monte Carlo Methods. Springer, London, England, ISBN-13:978-94-009-5821-0, pp: 99-177.

Hassan, R., A. Ibrahim, Z. Ahmad and M. Yusoff, 2014. Dowel-Bearing Strength Properties of two Tropical Hardwoods. In: InCIEC 2013, Rohana, H., M. Yusoff, Z. Ismail, N.M. Amin and M.A. Fadzil (Eds.). Springer, Singapore, Asia, ISBN:978-981-4585-01-9, pp: 27-36.

Kirkegaard, P.H., J.D. Sorensen, D. Cizmar and V. Rajcic, 2011. System reliability of timber structures with ductile behaviour. Eng. Struct., 33: 3093-3098.

Puaad, M.B.F.M., Z. Ahmad and S.A.K. Yamani, 2015. Derivation of Grade Stresses of Malaysian Tropical Timber in Structural Size. In: InCIEC 2014, Rohana, H., M. Yusoff, A. Alisibramulisi, N.M. Amin and Z. Ismail (Eds.). Springer, Singapore, Asia, ISBN:978-981-287-289-0, pp: 1117-1128.

Raychaudhuri, S., 2008. Introduction to Monte Carlo simulation. Proceeding of the 2008 Conference on Winter Simulation Conference, December 7-10, 2008, IEEE, New York, USA, ISBN:978-1-4244-2707-9, pp: 91-100.

Yasumura, M., J. Baroth and K. Kobayashi, 2012. Determination of failure mode of timber joints by Monte-Carlo simulation. Proceeding of 2012 World Conference on Timber Engineering, Vol. 1, July 16-19, 2012, WCTE, Auckland, New Zealand, pp: 377-384.

Yusoff, M., S.M. Shalji and R. Hassan, 2014. Particle Swarm Optimization for Single Shear Timber Joint Simulation. In: InCIEC 2013, Rohana, H., M. Yusoff, Z. Ismail, N.M. Amin and M.A. Fadzil (Eds.). Springer, Singapore, Asia, ISBN:978-981-4585-01-9, pp: 117-126.