

# Particle Swarm Optimization for Single Shear Timber Joint Simulation

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**Abstract** This paper presents a new paradigm that is possible to aid the traditional experimental analysis in timber joints research. Laboratory experiment has incurred a lot of cost and times to find optimize end distance of a timber joint. Particle swarm optimization (PSO) is applied and tested focusing on a single shear timber joints. The determination of fitness function is based on the findings from the previous datasets of the traditional laboratory experiments. The dataset includes the timber species of Kapur that emphasizes on 2D and 3.5D in diameter of end distance. Several PSO parameters were tested to find the maximum load carrying capacity of timber joint for different end distances. The findings show that PSO can give a feasible solution for a single shear strength timber joint performance. It demonstrates that the PSO has a potential to be used as a timber joint simulations that would be beneficial to timber joint researchers in predicting the load carrying capacity of a joint and contributes in reducing time and cost.

**Keywords** End distance · Fitness function · Kapur · Particle swarm optimization · Single shear · Timber joints connections

## 1 Introduction

Timber is one of the oldest and best-known structural materials, and one of the few renewable natural resources. It also is a desirable material for construction, building house or making furniture because it requires less energy to produce a

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usable end product than the other materials [1]. There are various species of timber in Malaysia such as Balau, Merbau, Kapur and Meranti. Timber species in Malaysia is grouped according to their strength and has been classified as strength group 1 to strength group 7 in MS 544: part 2: 2001 [2]. Strength group 1 is the strongest and as the strength group increased, the weaker the strength of the species. The timber species selected for this study is Kapur. Kapur species is categorised as medium hardwood and classified as strength group 4. This species is also considered as one of the easiest of supply and commonly use structural members. Nowadays, a cost for a timber is rising and it takes a long time to renew. Timber has been used as a structural material such as beam, column and roof trusses which brings to the use of fasteners and connections.

The competitiveness of a timber structure, relative to other building materials, may be determined by the efficiency of the connections. In most cases the fastening of timber to timber requires little skill or knowledge of design. Very limited publications about the tropical timber connections were found. The connection as reported are such as the shear and bending performance of structural, mortise and tenon connections for tropical timber [3–5].

Lacking of specific information for Malaysian timber in designing the load carrying capacity of joints and the influence of different end distance has led to this study. End distance is one of the major factors in designing the load carrying capacity of the timber connection. However, the actual load carrying capacity can only be determined using experimental work which incurred cost and time. This study emphasized in finding a simulation method in replacing the experimental laboratory testing method to determine and compare the ultimate shear strength of different end distance. Results of maximum load carrying capacity of single shear strength for Kapur joint compiled from previous laboratory work done by Abu Bakar [6] and Mat Nawi [7] has been taken for simulation. A lot of manual experiments are required to find the appropriate best end distance of a timber joint. Thus, this project aims of developing a system that can give feasible end distance of a timber joint without performing the manual experiment. With automated system, it will omit the cost and time as incurred in the experimental process.

The remainder of this article is organised as follows. Section 2 explains some related works. The PSO is discussed in Sect. 3. Experimental setup is introduced in Sect. 4. Computational results are analysed in Sect. 5; finally, Sect. 6 concludes the paper and presents certain avenues for future research.

## 2 Single Shear Strength

Shear strength is defined as the maximum load typically applied normal to a fastener' axis that can be supported prior to fracture. In other common term, the load is applied laterally to the fasteners. There are two typical shear strengths; single and double shear strength. Figures 1 and 2 show the single and the double shear strength [8]. Single shear is when load is applied in one plane that would

Fig. 1 Single shear joint

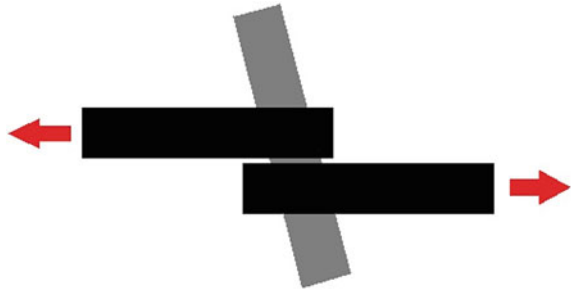
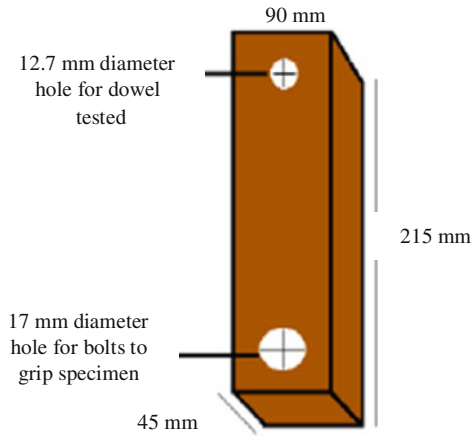
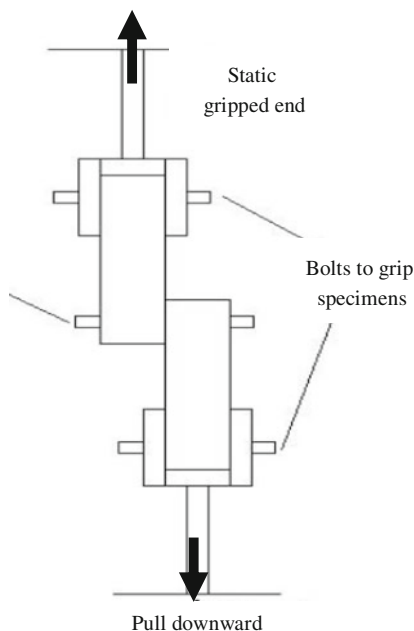


Fig. 2 Double shear joint



Fig. 3 The geometry of the timber specimen





**Fig. 4** The set up of the experimental pull-out test

result in the fastener being cut into two pieces meanwhile double shear is load applied in two planes that would result in three fastener pieces.

Method of single shear strength joint is an experiment to determine the maximum load carrying capacity of the joint. These joint can be fastened using the mechanical fasteners such as dowels, bolts and nuts and nails. The length of the centre of the mechanical fasteners to the end of the timber member is known as end distance. The end distance used in this study is at the length of 2 times the diameter ( $2D$ ) and 3.5 times the diameter of dowels ( $3.5D$ ). The diameter,  $D$  of the dowel is 12.7 mm (Fig. 3). The experimental set up is as shown in Fig. 4.

The performance of the two different end distances were also identified [6, 7] and compares the failure modes connection of different end distance based on European Yield Model (EYM) in National Design Specification, (NDS) 2005 [8]. This experiment use Kapur timber as a dowel. It also uses a different diameter of end distance to determine and compare the shear strength of Kapur timber. Figure 5 shows the example of result of  $2D$  and  $3.5D$  for load/deformation.

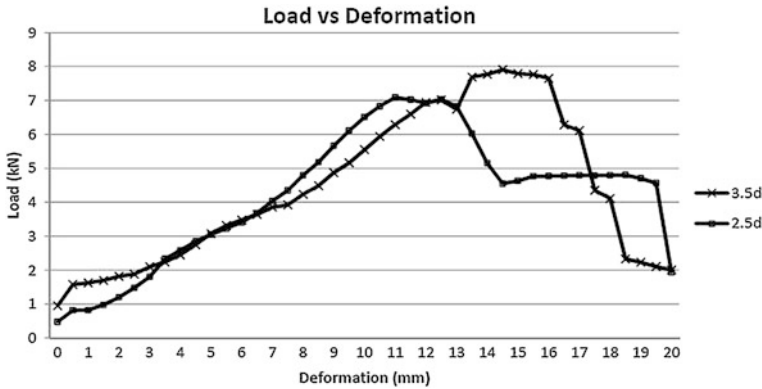


Fig. 5 Average 2D versus 3.5D end distance

### 3 Solution Using Particle Swarm Optimization

#### 3.1 Computational Solutions

This section highlights the steps involved in a proposed computational solution. The first step is on the data conversion. The data of manual experiment were converted into graph in excel. This is to compare current experiment result with this project result. The graph is then converted into polynomial. Equation from this conversion is used for fitness identification.

The next step is the application of Particle swarm optimization (PSO). The determination of fitness function is based on the findings from the previous datasets of the traditional laboratory experiments. It was then tested on dataset includes the timber species of Kapur that emphasizes on 2D and 3.5D in diameter of end distance. Several PSO parameters were tested to find the maximum load carrying capacity of timber joint for different end distances.

#### 3.2 Particle Swarm Optimization Implementation

PSO is an optimization approach proposed by Kennedy and Eberhart in 1995 inspired by social behavior of organisms such as a school of fishes and bird flocking [9, 10]. Each fish or bird is illustrated as a particle. Each particle moves stochastically in a search space for feasible solution. Each particle has its own velocity and position. PSO provides a mechanism that can process particle velocity and position in multi-dimensional space. Optimum feasible solution can be achieved by updating both velocity and position. The fitness values comprise of global ( $G_{best}$ ) and personal best ( $P_{best}$ ) derived from the simulated behavior of a

group of particles.  $Pbest$  is the best solution offered by each particle at local search area while the  $Gbest$  is the best solution on global scale.

PSO can be used to solve continuous and discrete problems [10, 11]. Canonical PSO algorithm has been used to solve continuous problems. Algorithm 1 shows PSO algorithm designed by [12].

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**Algorithm 1: PSO algorithm**

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1: Begin
2:   Initialize number of particles and populations
3:   Declare  $W$ ,  $C_1$  and  $C_2$ 
4:   Initialize  $V_{initialize(min)}$  and  $V_{initialize(max)}$ 
5:   Initialize  $D_{min}$  and  $D_{max}$ 
6:   Calculate  $Pbest$  and  $Gbest$  value for each particle
7:   Do
8:     For each particle
9:       Calculate new velocity value,  $V_{(new)}$ 
10:      Calculate new position,  $D_{(new)}$ 
11:      Calculate  $Pbest_{(new)}$ 
12:      Calculate  $Gbest_{(new)}$ 
13:   While (stopping condition is reached)
14: End

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The algorithm starts with the initialization of the population of particles or swarm size, followed by the initialization of inertia weight ( $W$ ) and acceleration constants ( $C_1$  and  $C_2$ ). Step 4 and 5 initialize the minimum value ( $V_{initialize(min)}$ ) and maximum value of velocity ( $V_{initialize(max)}$ ) and minimum position ( $D_{min}$ ) and maximum value of position ( $D_{max}$ ), respectively. Next is the calculation of  $Pbest$  and  $Gbest$  value for each particle. Step 9 calculates the new velocity value for each particle using Eq. 1. Step 10 updates the new position,  $D_{(new)}$  using Eq. 2. Finally,  $Pbest_{(new)}$  and  $Gbest_{(new)}$  are determined based on the fitness value set for the problem. Iteration starts from step 7 until step 13 to update the current velocity and position of each particle. This iteration will be done until it satisfies the stopping condition.

$$V_{id(new)} = W * V_{id} + C_1 * r_1 (Pbest_{(id)} - X_{id}) + C_2 * r_2 * (Gbest_{(id)} - X_{id}) \quad (1)$$

$$X_{id(new)} = X_{id} + V_{id(new)} \quad (2)$$

where:

$V_{id(new)}$	new velocity of the $i$ th particle in $d$ th dimension
$V_{id}$	current velocity of the $i$ th particle in $d$ th dimension
$X_{id}$	current position of the $i$ th particle in $d$ th dimension
$X_{id(new)}$	new position of the $i$ th particle in $d$ th dimension
$W$	inertia weight

$C_1$ and $C_2$	acceleration coefficient
$r_1$ and $r_2$	random function in the range of [0,1]
$Pbest_{(id)}$	position of the personal best of the $i$ th particle in $d$ th dimension
$Gbest_{(id)}$	position of the global best derived from all particles in the swarm.

PSO has the capability to explore regions in the specified search space and exploit the search to refine feasible solutions. These search strategies are influenced by the following parameters; acceleration constants ( $C_1$  and  $C_2$ ) and inertia weight [13, 14] that has been applied in the PSO algorithm.

Cognitive component,  $C_1 * r_1 * (Pbest_{(id)} - X_{id})$  is a combination of acceleration coefficient ( $C_1$ ), random function, and the difference between the old position and personal best position in the local search area. This component reflects the performance of the individual particle  $i$ , from the past performance [13].

Social component,  $C_2 * r_2 * (Gbest_{(id)} - X_{id})$  consists of acceleration coefficient ( $C_2$ ), random function, and the difference between the old global position and the global best position after every iteration. This component reflects the performance of the particle  $i$  from the past performance that are obtained from all particles in the global search space. Both of these components have stochastic flavor with the contribution of  $C_1 * r_1$  and  $C_2 * r_2$  [13, 15]. As far as velocity update is concerned, the new velocity relies on these components and the inertia weight to ensure the velocity remains in the same direction as the previous velocity. Thus, the setting of these parameters is important to optimize the search space.

## 4 Experimental Setup

This section discusses the experimentation preparation. The data of manual experiment were converted into graph in excel. The purpose of converting data into coordinate graph is to compare current experiment result with this project result.

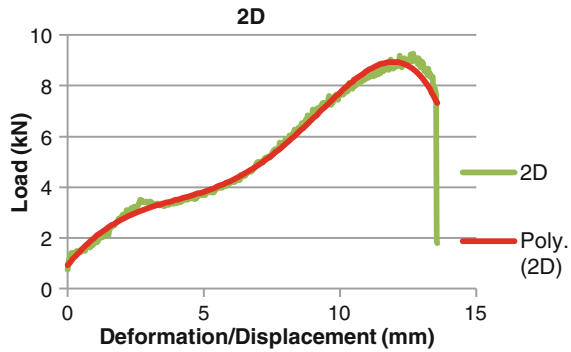
To find an equation, the graph is converted into polynomial. The Fig. 6 shows the conversion from the data obtained from laboratory experiment to polynomial for the 2D.

The fitness equation that used in this PSO is based on diameter of end distance in timber joint experiment. Table 1 shows fitness function for 2D and 3.5D. Table 2 is the parameter setting for the PSO parameters.

## 5 Results and Findings

This section discusses the results from the computational experiment of the PSO implementation. Table 3 demonstrates results for 2D using different numbers of iterations. The results show that the maximum end distance obtained at 5th iteration with 8.778. However, 10th and 15th iterations give low end distance value.

**Fig. 6** Polynomial graph for 2D



**Table 1** Fitness function

End distance diameter	Fitness function
2D	$y = -0.0001x^5 + 0.0017x^4 + 0.0142x^3 - 0.2484x^2 + 1.3387x + 0.9129$
3.5D	$y = 0.0000029394x^6 - 0.0001720764x^5 + 0.0034772430x^4 - 0.0311259334x^3 + 0.1556688226x^2 - 0.0507105690x + 1.7557687041$

**Table 2** Parameter setup

Parameter	Value
Inertia weight	0.0 – 1.0
$C_1$	2.0
$C_2$	2.0
Initial $V_{initialize(min)}$	-1
Initial $V_{initialize(max)}$	1
Number of particles in a swarm (population)	30
Stopping condition	Iteration equal to 10

**Table 3** Result for 2D using velocity of -1 to 1

Velocity	Iteration	X	Y	Maximum end distance (mm)
-1 to 1	5	12.518	8.778	<b>8.778</b>
-1 to 1	10	10.870	8.494	8.494
-1 to 1	15	9.537	7.251	7.251

A few tuning processes were performed to find the most optimal solutions. For 2D, the velocity parameter was adjusted between ranges -3 to 3 and it provides better solution with the maximum of 8.839 end distance at 5th iterations as shown in Table 4.

Table 5 shows the results of 3.5D using velocity value between -1 and 1. The result also shows the maximum value for the end distance is at 5th iteration. The result seems similar to 2D by using the same parameter settings. The tuning process



**Table 4** Result for 2D using velocity of  $-3$  to  $3$ 

Velocity	Iteration	X	Y	Maximum end distance (mm)
$-3$ to $3$	5	12.4059	8.83882	<b>8.83882</b>
$-3$ to $3$	10	10.3491	8.05963	8.05963
$-3$ to $3$	15	9.30713	7.01025	7.01025

**Table 5** Result for 3.5D using velocity of  $-1$  to  $1$ 

Velocity	Iteration	X	Y	Maximum end distance (mm)
$-1$ to $1$	5	16.3331	10.0853	<b>10.085</b>
$-1$ to $1$	10	16.2508	10.0844	10.084
$-1$ to $1$	15	16.3579	10.0851	10.085

**Table 6** Result for 2D using velocity of  $-4$  to  $4$ 

Velocity	Iteration	X	Y	Maximum end distance (mm)
$-4$ to $4$	5	16.2697	10.0848	10.085
$-4$ to $4$	10	16.3333	10.0853	<b>10.085</b>
$-4$ to $4$	15	16.3568	10.0851	10.085

is done with the minimum velocity of  $-3$  and maximum velocity of  $3$ . For 2D, the velocity parameter was adjusted between ranges  $-3$  to  $3$  and ranges of  $-4$  and  $4$ , it provides similar results compared to velocity ranges between  $-1$  and  $1$ . Table 6 provides consistent results with the maximum of  $10.085$  mm of the end distance.

The results show that the employment of PSO to find the maximum end distances for single shear strength is possible. The maximum end distance obtained is within the range that of obtained from the lab experiments. At only 5th iteration and swarm size of  $30$ , PSO offers good performance for the single shear timber joint connection.

## 6 Conclusion

The PSO implementation to find possible end distance in a single shear timber joints demonstrates the capability of PSO in solving the optimization problem. The results of 3.5D using velocity value between  $-1$  and  $1$  show the maximum value for the end distance is at 5th iteration. The result seems similar to 2D by using the same parameter settings. For 2D, the velocity parameter was adjusted between ranges  $-3$  to  $3$  and ranges of  $-4$  and  $4$ , it provides similar results compared to velocity ranges between  $-1$  and  $1$ . For the particular single shear timber joints, PSO able to obtain the end distance value that accommodates the range provided from the laboratory experiment. The ability of PSO to provide solutions would help the timber researcher in reducing time and cost of material for lab experiment.

However, testing on PSO should consider different types timber, joints, and composites may provide a better computational simulation results.

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## References

1. D.W. Green, Strength and stiffness. Wood, 1–5 (2001)
2. MS 544: Part 2, Malaysian Standard. Code of Practice for Structural use of Timber. Department of Standards Malaysia. SIRIM (2001)
3. H. Rohana, I. Azmi, A. Zakiah, Shear and bending performance of mortise and tenon connection fastened with dowel. J. Trop. For. Sci. **22**(4), 425–432 (2010)
4. H. Rohana, I. Azmi, A. Zakiah, Bending behaviour of dowelled mortise and tenon joints in kempas. Sci. Res. J. **5**(1), 1–11 (2008). ISSN 165-7009
5. H. Rohana, I. Azmi, A. Zakiah, Shear capacity of dowelled mortise and tenon joint in tropical timber. J. Inst. Phys. Lop Conf. Ser.: Mat. Sci. Eng. **17**(1), 1–11 (2010)
6. M. H. Abu Bakar, *Single shear strength of kapur in influence of end distance: 2.5D versus 3.5D*. Unpublished project report (Faculty of Civil Engineering, Universiti Teknologi MARA, 2012)
7. N. W. Mat Nawi, *Single shear strength of kapur in influence of end distance: 2D versus 2.5D*. Unpublished project report (Faculty of Civil Engineering, Universiti Teknologi MARA, 2012)
8. NDS, *National Design Specification for Wood Construction* (American Forest and Paper Association (AFPA), Washington D.C., 2005)
9. J. Kennedy, R. Eberhart, *Particle Swarm Optimization*, (1995)
10. J. Kennedy, *The Particle Swarm: Social Adaptation of Knowledge*, (1997) pp. 303–308
11. M. Yusoff, J. Ariffin, A. Mohamed, *Solving Vehicle Assignment Problem Using Evolutionary Computation*. in *Advances Swarm Intelligence*, vol 1 (Springer, Berlin, 2010), pp. 523–532
12. M. Yusoff, J. Ariffin, A. Mohamed, Discrete particle swarm optimization with a search decomposition and random selection for the shortest path problem. J. Comput. Inf. Syst. Ind. Manag. Appl. **4**, 578–588 (2012)
13. J. Venter, J. Sobieszczanski-Sobieski, Parallel particle swarm optimization algorithm accelerated by asynchronous evaluations. J. Aerosp. Comput. Inf. Commun. **3**(3), 123–137 (2006)
14. A.P. Engelbrecht, *Computational Intelligence: An Introduction* (Wiley, New York, 2007)
15. Y. Shi, Yuhui, R.C. Eberhart, Empirical study of particle swarm optimization. *Evolutionary Computation, CEC 99. Proceedings of the 1999 IEEE Congress on*, vol 3 (1999)