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# Evaluation of particle swarm optimization for strength determination of tropical wood polymer composite

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## Article Info

## ABSTRACT

A wood-polymer composite (WPCs) refers to wood-based components that are coupled with polymers to produce a composite material. Obtaining the best strength for the tropical WPCs is still a lack of research mainly for the tropical timber species and require a large consumption of time and cost. This paper highlighted the evaluation of particle swarm optimization (PSO) to assist in finding the optimal value of the composition of tropical WPCs to obtain the best strength that would offer a betterment in a quality product of WPCs. The findings demonstrate that PSO has been shown as a viable and efficient method for WPCs strength. The composition of Sentang, wood sawdust of 50%, HDPE of 49% and 1% coupling agent is demonstrated the best strength for the WPC. The employment of PSO as an assisted tool would give significant benefit to the manufacturer and researcher to determine the composition of material with less cost and time.

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## 1. INTRODUCTION

Wood and polymer are the major elements of wood-polymer composite (WPC). Wood is the most versatile product on the planet with many thousands of distinct uses [1]. Wood itself contains polymers such as lignin, cellulose, and varied hemicellulose. However, it has distinct features from the synthetic polymers with which it is commonly paired. Wood is affordable, steeper and harder than synthetic polymers, rendering it useful for mixing or reinforcing. Although wood does not decrease and grow significantly with temperature, it readily absorbs moisture, which changes its features and dimensions and can lead to biodegradation if not shielded [2]. The word "polymer" is widely used in the plastics and composites sector today and is often used as a synonym for "plastic" or resin. A polymer is a chemical compound that binds molecules together in long repeating chains. Polymers have distinctive characteristics that can be tailored to distinct applications. One of the benefits of woodpolymer composites is water-resistant. With this regard, WPCs are often used in the building of indoor and outdoor equipment, automobiles, furnishings, highway equipment and consumer goods.

Current design of WPCs focuses on enhancing material characteristics varying from hardness to product durability as well as enhancing matrix component alignment for longer-lasting products.

There is a need for the examination of the environmental consequences and efficiency effects of WPCs [3]. Therefore, in order to meet all the requirements for current work in WPCs, a lot of experimentation needs to be done to identify the best result of the strength and quality of the composition material used in wood polymer. Finding an optimal value of the strength and quality of the composition material for wood polymer is not an easy work. Multiple experiments need to be conducted. It is therefore needs many procedures to determine the strength of WPCs through experimentation. It will which, require a lot of time, equipment and costs and labor to conduct experiments regularly in laboratories. Whilst, the computational optimization method has proven its usefulness in many optimization problems [4-11] including manufacturing, scheduling, evacuation planning and travelling salesman problem. The approach aims to obtain the best composite for timber usages in polymer composites. Some researches worth mentioning are Genetic Algorithm (GA) for timber strength optimizer [12], PSO for timber tensile strength [13], modelling nonlinear behaviour with artificial neural networks, adaptive neuro-fuzzy inference systems and genetic programming [14], composites material using hybrid GA and Artificial Neural Network (ANN) [15-16], identification of nano reinforcement and quality assessment of composites [17], estimate the performance of ethylene polymerization over this type of new metallocene/post-metallocene multisite catalysts using ANN and support vector machine [18]. Inspired by these idea, this paper discusses the potential of using an artificial intelligence method, namely particle swarm optimization (PSO) to assist in finding an optimal composition of a good strength of tropical WPCs.

## 2. CONSTRUCTION OF PARTICLE SWARM OPTIMIZATION (PSO)

### 2.1. Data acquisition

Datasets were obtained from the list of attributes for WPCs data. The attributes are:
−   Wood species: Rubberwood and Sentang, $X_1$
−   Wood type: leaves, branch, and trunk, $X_2$
−   Type of polymer: High-density polyethylene (HDPE), $X_3$
−   Coupling agent: Maleated Anhydride, $X_4$
−   Tensile strength test: Modulus of Rupture (MOR), $X_5$

Experiments were performed with some of possible composition of the above attributes to investigate the strength of the WPCs for both types of tropical timbers flour, Rubberwood and Sentaing. Table 1 shows sample data for tensile strength test of Sentang and Rubberwood tree obtained from the laboratory experiment that was experimented in Faculty of Applied Sciences, Universiti Teknologi MARA. The ratio of wood sawdust ($X_3$), polymer (HDPE) ($X_4$) and coupling agent ($X_5$) are considered.

Table 1. Sample dataset for tensile strength test of Sentang and Rubberwood tree from laboratory experiments

| Ratio ($X_3$: $X_4$: $X_5$) | Type | MOR (Mpa) | |
|---|---|---|---|
| | | Sentang | Rubberwood |
| 25:74:1 | Leaves | 16.052 | 17.2075 |
| | Branch | 16.73 | 20.7275 |
| | Trunk | 17.054 | 20.6875 |
| 35:64:1 | Leaves | 18.024 | 19.7225 |
| | Branch | 22.476 | 21.15 |
| | Trunk | 26.678 | 23.035 |
| 45:54:1 | Leaves | 20.262 | 18.93 |
| | Branch | 25.46 | 23.405 |
| | Trunk | 27.908 | 26.185 |
| 0:100:0 | HDPE | 15.158 | 14.61 |

### 2.2. Solution mapping

The development PSO requires a representation of the problem [19]. We represent using a discrete and binary value and it addresses the wood species, wood types, ratio of wood, ratio of polymer and ratio of coupling agent. Figure 1 is the particle representation for PSO. The range is based on the datasets obtained from the laboratory test and theoretical approach possibility from previous research and experts in composite polymer.

Following, are the notations used in the mathematical formulation:

Indices:
$i$  :  Wood species
$j$  :  Wood types

Decision variables :

| | | | |
|---|---|---|---|
| $X_{1i}$ | : | Type of wood species $i$; $i$ = {1, 2} | 1; if it is Rubberwood. |
| | | | 2; if it is Sentang. |
| $X_{2j}$ | : | Wood types $j$; $j$ = {1, 2, 3} | 1; if it is trunk. |
| | | | 2; if it is branch. |
| | | | 3; if it is leaves. |

Particle representation:

| X₁ | X₂ | X₃ | X₄ | X₅ |
|---|---|---|---|---|
| [1-2] | [1-3] | [0 -50] | [0-100] | [0-1] |

Figure 1. Solution mapping for the tropical WPCs

Where as,
$X_1$: Wood species [1-,Rubberwood 2- Sentang]
$X_2$: Wood types [1- Trunk, 2- Branch, 3-Leaves]
$X_3$: ratio of wood sawdust [%]
$X_4$: ratio of polymer HDPE [%]
$X_5$: ratio of coupling agent (Maleated Anhydrite) [%]

## 2.3. Fitness function

The determination of fitness function was based on the test result from the laboratory experiment. Equation (3) is a fitness function to measure the tropical WPCs composition and randomly applied in PSO.

*Maximize*

$$WPCs = \sum_{i=1}^{2} X_{1i} + \sum_{j=1}^{3} X_{2j} + ...$$

Where as,
$X_3 + X_4 + X_5 = 100$

## 2.4. PSO steps for WPCs composition

PSO as one of the swarm intelligence methods has shown popularity in many many optimization problem domains. This work adopted the PSO from the previos work [20-24].
Step 1: the algorithm starts with the initialization of the population of particles or swarm size,
Step 2: initialize the inertia weight ($W$) and acceleration constants ($C_1$ and $C_2$).
Step 3: initialize the minimum value ($V_{initialize(min)}$) and maximum value of velocity ($V_{initialize(max)}$)
Step 4: initialize the minimum position ($D_{min}$) and maximum value of position ($D_{max}$)
Step 5: calculate *Pbest* and *Gbest* value for each particle
Step 6: iteration starts from here until step 10
Step 7: calculate the new velocity value for each particle using Equation 1
Step 8: updates the new position, $D_{(new)}$ using Equation 2
Step 9: calculate *Pbest* $_{(new)}$ and *Gbest* $_{(new)}$ based on the fitness value set for the problem
Step 10: update the current velocity and position of each particle.
Step 11: the algorithm is finished. The best solution found when the fitness is recorded as the best fitness.

PSO has the capability to explore regions of the search space and exploit the search to refine a feasible solution. These search strategies are influenced by the parameters; acceleration constants ($C_1$ and $C_1$) and inertia weight (Shi & Eberhart 1999; Engelbrecht 2007) that has been applied in the PSO algorithm. Equations (1) and (2) present the velocity and position formulas for the canonical PSO, respectively.

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

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

Where as,

$V_{id(new)}$ = 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.

## 3. RESULTS AND DISCUSSION

A details analysis of the outputs produced by the PSO is reported regarding its performance, on how parameters of PSO gives an impact in finding good solution.

### 3.1. Parameter setting

The selection of parameters was handling based on the parameter's selection suggested from previous work. PSO is a problem dependent algorithm, thus the computational experiments were done using the ranges of the parameter setting as indicated in Table 2.

Table 2. Parameter Setting

| Parameter | Value |
|---|---|
| Iteration | 10, 20, 30 |
| Particles | 10, 20, 30, 40, 50 |
| Weight | 0.5, 0.6, 0.7, 0.8, 0.9 |
| Coefficient, $C_1$ | 0.5 |
| Coefficient, $C_2$ | 0.9 |

### 3.2. Computational Experiment Based on Iteration and Swarm Sizes

The different number of population size of 10, 20, 30 and 40 are evaluated using the WPCs datasets consist of a range of 1-2 wood species, 1-3 wood types, 0-50 ratio of wood, 0-100 ratio of polymer and 0-1 ratio of coupling agent. The number of iterations is 10, 20 and 30. The inertia weight = 0.8 and a coefficient factor of $C_1 = 0.5$ and $C_2 = 0.9$ are constant. The result was demonstrated in Table 3. The performance of PSO based on iteration number and population size.

Table 3. Computational results with 10, 20 and 30 iterations and different numbers of swarm sizes

| Iteration | Swarm Sizes | WPCs Composition | Fitness Value (MOR) |
|---|---|---|---|
| 10 | 10 | [ 2 2 48 51 1] | 27.879 |
| | 20 | [ 2 1 47 52 1] | 28.709 |
| | 30 | [ 1 1 47 52 1] | 26.986 |
| | 40 | [ 2 1 48 51 1] | 29.109 |
| | 50 | [ 1 1 50 49 1] | 28.186 |
| 20 | 10 | [ 2 1 50 49 1] | 29.909 |
| | 20 | [ 2 1 46 53 1] | 28.308 |
| | 30 | [ 2 1 50 49 1] | 29.909 |
| | 40 | [ 1 1 49 50 1] | 27.786 |
| | 50 | [ 2 1 50 49 1] | 29.909 |
| 30 | 10 | [ 1 1 47 52 1] | 26.986 |
| | 20 | [ 2 1 42 57 1] | 26.707 |
| | 30 | [ 1 1 50 49 1] | 28.186 |
| | 40 | [ 1 1 48 51 1] | 27.386 |
| | 50 | [ 2 1 50 49 1] | 29.909 |

In the iteration = 10, using different swarm sizes, 10, 20, 30, 40 and 50 to identify the optimum value of WPCs has been done. The result shows that the best result recorded was 29.109. However, when using iteration number = 20, swarm sizes = 30 and 50, the results improved to 29.909. Also, the same results for 30 iterations and swarm sizes =50. From these computational results, it is interesting to note that with the more iterations used, it gives the effect on the speed of convergence towards the achievement of the optimum solution. It is demonstrated that the sarcastically flavor of PSO that carried out the balancing of searching for

both exploitation and exploration affect the results. In addition, the choice of parameters plays an important role to obtain an optimal solution. In terms of the composition, the use of Sentang and its trunk flour is the most selected for the best solutions whereas Sentang is being less selected. It is demonstrated Sentang provides less strength for WPCs. In addition, the use of the trunk and leaves are least to be selected.

### 3.3. Computational experiment based on inertia weight

The different of inertia weight have been experimented consist of 0.6, 0.7, 0.8 and 0.9. The constant parameter is C1 = 0.5, C2 = 0.9 based on number of iterations = 20. The optimal result of WPCs is recorded at 20 iterations and 30 particles with inertia weight, 0.8 which is 29.909. Sentang and branch part is chosen. The results show the solution is getting better when the inertia weight is increasing. However, at 20 iterations and 10 particles recorded the highest value is 29.109 with inertia weight, 0.6 and 0.7 but the solution does not reach the optimum value. The details is shown in Table 4.

Table 4. Computational results using different values of inertia weight

| Swarm Size | Inertia Weight | WPCs Composition | Fitness Value (MOR) |
| --- | --- | --- | --- |
| | 0.6 | [ 2 1 48 51 1] | 29.108 |
| 10 | 0.7 | [ 2 1 48 51 1] | 29.109 |
| | 0.8 | [ 2 3 48 51 1] | 26.649 |
| | 0.9 | [ 1 1 44 54 1] | 25.633 |
| | 0.6 | [ 1 1 48 51 1] | 27.386 |
| 30 | 0.7 | [ 2 1 49 50 1] | 29.509 |
| | 0.8 | [ 2 1 50 49 1] | 29.909 |
| | 0.9 | [ 1 1 49 50 1] | 27.786 |

### 3.4. Computational experiment based on coefficient value

The best parameter setting that suited the problem of WPCs after performing a few of the experiments with the tuning parameters. The suitable parameters are, iteration number = 20, swarm size = 30, inertia weight = 0.8 and C1 = 0.9 and C2 = 0.5, respectively as indicated in Table 5. The optimum value of tensile strength is 29.909 as of [2 1 50 49 1] where the material used is 50% of Sentang with wood sawdust, 49% of HDPE and 1% of Maleated Anhydrite.

Table 5. Different Coefficient Value using 20 Iterations and Swarm Size = 30

| $C_1$ | $C_2$ | WPCs Composition | Fitness Value (MOR) |
| --- | --- | --- | --- |
| 1 | 1 | [2 1 48 51 1] | 29.109 |
| 0.9 | 0.5 | [2 1 50 49 1] | 29.909 |
| 0.5 | 0.5 | [2 1 48 51 1] | 29.109 |

It is also proved that PSO that this algorithm has faster speed of convergence and acceleration to find optimum values [25-27]. By using PSO, the swarm size within the range of 10 to 30 as normally reported based on benchmark solutions.

### 4.    CONCLUSION

The application of PSO has been shown as a viable and efficient method to overcome traditional laboratory cost and time consumption. This positive potential has proofed the popularity of PSO in finding an optimal solution. The determination of the best combination of tropical WPCs to measure its strength assisted by PSO gives guidance for the selection of materials. Searching capability of PSO includes the exploration and exploitation demonstrated some balancing in the process of finding better solutions. In addition, the use of suitable parameter settings during the evaluation is considered as a major factor PSO to offer an optimal or near optimal solutions. In future, the improvement of the PSO or hybridation with other artificial intelligence methods as such of local search, cuckoo search and firefly. The work also can be tested with another type of wood polymer composite to support manufacturing industries and research in product development.

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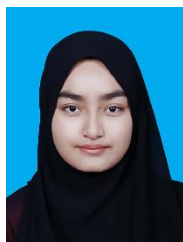
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