Integrated ANN And Bidirectional Improved PSO For Optimization Of Fertilizer Dose On Palawija Plants

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***Abstract*—With the rapid advance of Science and Technology, especially in the field of agriculture. One of the most important aspects that are critical in agriculture is fertilizer. Within the application of fertilizer itself, there are many types of fertilizers and a combination of different doses. Whereas palawija is a plant for crop rotation, that is planted after the rice cultivating season. Palawija is also grown in the highlands where rice cannot grow. Fertilizer application can give different impacts for Palawija. This paper will explain that with an Integrated Artificial Neural Network (ANN) and Bidirectional Improved Particle Swarm Optimization (BIPSO) can optimize the fertilizer dose on Palawija plants. The ANN method can be used to determine the effect on the plants arising from fertilizer application. After this, the user can input two of the effects on crops selected for optimization doses of fertilizer using BIPSO. The ANN method proved to be very good at predicting the value using training data and BIPSO is able to optimize the more than one vector thus fastening the process of the system. The smallest MSE value 8.6023E-03 is obtained from the test using 90% training data and 10% test data, iterating 100 times, with the number of hidden neuron at 10, learning rate of 0.6 and momentum of 0.6. The parameter values of BIPSO use standard parameters on Particle Swarm Optimization (PSO). The proposed method give the recommendation that to get the plant dry weight 4.4964 ton/ha and yield 6.99985 ton/ha is needed Urea 0.191 ton/ha or 191 kg/ha, SP_{36} 0.201 ton/ha or 201 kg/ha, KCL 0.288 ton/ha or 288 kg/ha and Biochar 48.3 ton/ha.**

Keywords—artificial neural network; bidirectional improved PSO; fertilizer dose; optimization; palawija

I. INTRODUCTION

The advancement of technological and agricultural sector followed with an ever growing population, have an impact on the need for food and other agricultural products as the cost of these products continue to rise developing countries face the problem of food quantity, whereas developed countries face the problem of food quality where it can be indicated with the influence of several factors, one of which is the granting of fertilizer dose that is excess or shortage or lack of proper to the plants, which makes yield when it has become a basic ingredient of food, are not healthy and not optimal nutrient when consumed, and than environmental pollution and production cost efficiency that high product competitiveness. This is the challenge that must be faced today by Science and Technology through research in all aspects of agriculture.

One aspect of improving agriculture is through the use of fertilizers. Fertilizers are needed because the land is not able to naturally fulfill the required nutrients for crops. Fertilization is also done in an effort to meet production needs. However, if fertilization is done excessively it will have a negative impact towards the environment and increase the cost of production, which in turn will reduce the competitiveness of products hence fertilizers should be used wisely. The effective use of fertilizers will be achieved when there is a sufficient level of technology and an adequate knowledge of plants, nutrients, and the environment. Therefore, attention to the optimal dosage is very important for fertilization.

Optimal dosing involves many combinations of types of fertilizers. It's important to pay attention to the type of fertilizer that is safe for the environment. The combination of the type of fertilizer produces different effects on plants. To get a combination of fertilizers with the results expected to be solved by the algorithm Particle Swarm Optimization (PSO). In [1], PSO is used to optimize the parameters FKNN and feature selection using the Time-varying inertia weight (TVIW) and Time-varying acceleration coefficients (TVAC) has been applied in the case of bankruptcy prediction, the both of time variant that is used to control the ability of PSO in local search and accelerate to the global optimum solution based on double fitness value which consists of accuracy value and number of selected features. The results obtained by PSO are able to produce an optimal solution because of the balance between exploitation and exploration [2].

In addition, a new approach to the optimization problem is with the integration method of an Artificial Neural Network (ANN) with Bidirectional Improved Particle Swarm Optimization. Currently, this algorithm is used to improve the optimization of the manufacturing of roof cement. In determining the quality of cement, steel pressing process is carried out. The problem is that it is difficult to determine the quality of the resulting roof cement. Because of these problems, the manufacturer then has to revert to the traditional approach that is based on skills and human judgment, but this approach raises issues of work delays, waste and error assurance that the decision is taken to determine whether or not the pressure of steel is optimal. So ANN is used to determine cement quality of process parameter using the input values given, then BPSO optimizes the value of quality of the

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roof cement chosen so that it produces the best output. From the results of tests performed, there was an increase in yield from 60% to 97%. In [3], IPSO-SVR proved successful exploration to improve the process speed and accuracy of the solution. From the test results, it is shown that the role of the IPSO algorithm not only ensures rapid convergence when compared to the regular PSO but is also very efficient as an improvement method.

This study implements the integration of ANN and BIPSO in determining the required dose in providing a combination of fertilizers. ANN is used to determine the influence exerted by various combinations of fertilizers. Afterward, BIPSO will optimize the dose of fertilizer, in accordance with the primary influence needed by farmers.

II. METHOD

The general diagram of the optimization process within the integration of ANN and BIPSO is shown in Fig. 1. The first step is to retrieve data from a field in the form of pairing between treatments of X_k and the outcomes of Y_i, then the training process done with ANN to identify modeling the optimal weight to determine the effects of the physical plant (Y_i). The second step is to optimize the output of Y_i in accordance with the expected results by the user, eg optimization *BK* and *HP* using algorithms ANN-BIPSO to give the best mixtures and needs as treatment recommendation (X_k). Each type of fertilizer is given 6 treatments with different combinations of fertilizers dose based on experience, and each dose combinations treatments is repeated 30 times, so the total amount of data in the dataset is 180 treatments.

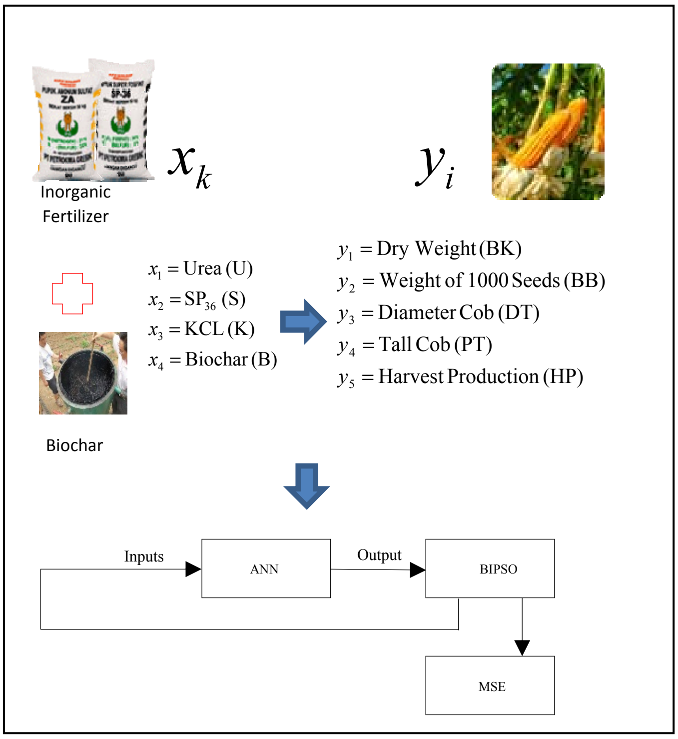

Fig. 1. The general diagram of the optimization process

A. BackPropagation Neural Network

Fig. 2 shows the architecture of backpropagation NN used in this study. There are three steps that must be done during training; the feed forward phase, the propagation phase, and phase changes in the weights [4].

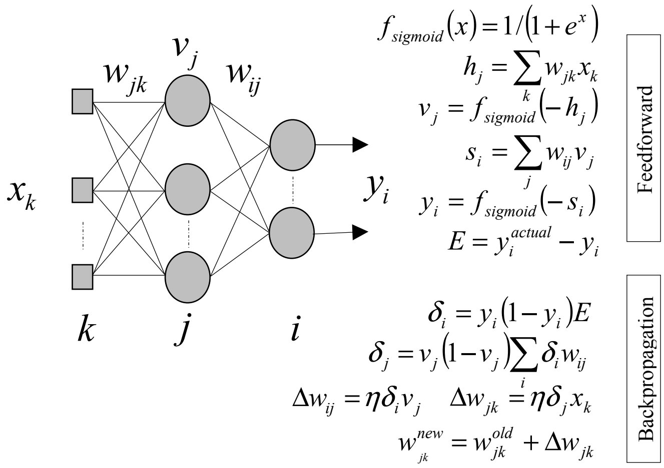

Fig. 2. Backpropagation architecture

Data normalization (1) is the process to scale the data so that the data is within a range of specific value. The method of data normalization that is used in this study is the Min-Max method [5].

$$x' = \left(0.8 * \frac{x - \min value}{\max value - \min value}\right) + 0.1 \tag{1}$$

Where x is actual data, x' is the result of normalization, *min value is* the min value of the data and *max value* is the max value of the data.

The research conducted by Shibata and Ikeda (2009), examines the effect of the stability of the concealed or hidden layer neuron in a neural network learning process. It is applied in mapping the problem of random numbers. The formula for determining the number of hidden nodes or hidden neuron is (2).

$$p = \sqrt{n * m} \tag{2}$$

Where p is the number of hidden neuron, n is the number of the input layer and m is the number of the output layer.

B. Bidirectional Improved Particle Swarm Optimization (BIPSO)

PSO algorithm was first developed by Zhang and Huang. This method is used because it can provide a solution with good distribution in solving various problems of testing standards [6][7]. In general, the basic principle is to train BIPSO so that each particle simultaneously looks at their neighbors in an area where the particles are rarely distributed by combining search strategies and a search strategy for isolated neighbors. Fig. 3 shows the general flow of the ANN-BIPSO algorithm.

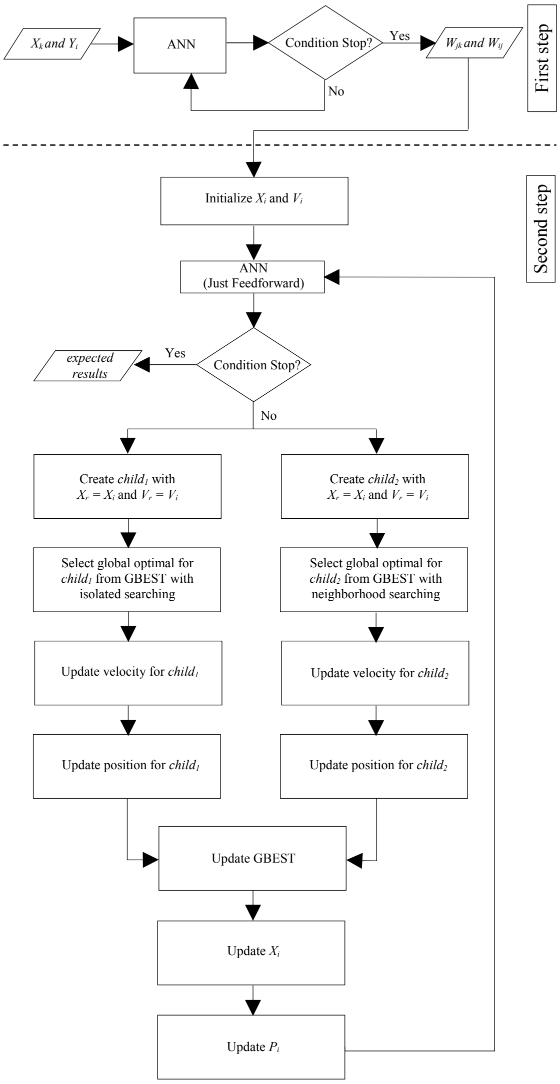

Fig. 3. Proposed approach of ANN-BIPSO

C. Initialization

Initialization of particles to population (eg 30 swarms and 8 GBEST, see Table I) and its collection is stored with the position and velocity vectors at random. The position of each particle for each dimension k-th are generated randomly with a range of values [$x_{k,min}$, $x_{k,max}$] that have previously been provided by experts. As for the range of velocity values [$-V_{max}$, V_{max}] this can be calculated using the following (3).

$$V_{\max} = 60\% * x_{k,\max} \tag{3}$$

Target vector evaluation is $F = (f_1, f_2)$ where f_1, f_2 obtained by the equation minimization (4).

$$f_1 = \frac{1}{y_1(x)} \qquad f_2 = \frac{1}{y_5(x)} \tag{4}$$

Description:
$y_1(x)$ = expected results of Dry Weight
$y_5(x)$ = expected results of Harvest Production

TABLE I. INITIAL PARTICLES AS GBEST

Particles	x_1	x_2	..	x_5	NC	f_1	f_2
X_1							
..	..	..	..	..	..	..	..
X_8	..	..	..	..	..	..	..

where $X_i = (x_{i1}, x_{i2}, \ldots x_{id})$, d is number of feature.

Then determine the dose range and boundary, lower and upper bound at the growth of the plants so that optimization is still within a feasible range value for applied value and for the good growth, namely, 0.177 ≤ Urea ≤ 0.533 ton/ha, 0.0138 ≤ SP36 ≤ 0.319 ton/ha, 0.04 ≤ KCL ≤ 0.3 ton/ha, 10 ≤ Biochar ≤ 50 ton/ha, Dry Weight = 4-5 ton/ha, weight of 1000 seeds = 4-5 ton/ha, Diameter cob = 3-5 cm, Tall cob = 13-20 cm, and Harvest Production = 6-8 ton/ha.

D. Generate Offspring Particle

There are two children called $child_1$ and $child_2$ which will be raised for each particle. The position and speed of child are fully inherited from its parent. With (5) and (6) that assumed $child_1$ and $child_2$ are derived from particle, their position and speed are denoted by X_l, X_r, V_l, V_r.

$$X_i = X_l = X_r \tag{5}$$
$$V_i = V_l = V_r \tag{6}$$

Description:
X_i = the position of the particle
X_l = the position of the particle $child_1$
X_r = the position of the particle $child_2$
V_i = velocity of the particle
V_l = velocity of the particle $child_1$
V_r = velocity of the particle $child_2$

E. Search GBEST and PBEST for $child_1$

For each member of the GBEST, niche count (NC) is calculated using the isolated searching strategy with the following (7) [7].

$$d_{ij} = \sqrt{\sum_{t=1}^{n} (f_t(x_i) - f_t(x_j))^2} \tag{7}$$

Description:
d_{ij} = euclidean distance
i = 1,2,..,p
j = 1,2,..,p $\quad i \neq j$

then the value of the share function is calculated by the following (8).

$$s(d_{ij}) = \begin{cases} 1 - \dfrac{d_{ij}}{\sigma_{share}} & d_{ij} < \sigma_{share} \\ 0 & d_{ij} > \sigma_{share} \end{cases} \tag{8}$$

Equation (9) and (10) is used to calculate the niche radius.

$$\sigma_{share} = \frac{r}{\sqrt[p]{q}} \tag{9}$$

$$r = \frac{1}{2}\sqrt{\sum_{k=1}^{p}\left(x_{k,\max} - x_{k,\min}\right)^2} \quad (10)$$

R = radius
p = the number of input parameters GBEST
k = input index of GBEST
$x_{k,\max}$ = the max of input parameters GBEST
$x_{k,\min}$ = the min of input parameters GBEST
q = the count of member GBEST

σ_{share} is niche radius that means a penalty or fitness value to reduce the value of diversity in the population to reduce the appearance of descent or the next generation. Furthermore, niche count (11) for the equation to members of GBEST i = 1,2,..,p.

$$niche(i) = \sum_{j=1}^{p} s\left(d_{ij}\right) \quad (11)$$

Members with the smallest value of NC will be chosen as the GBEST to $child_1$. While the value of PBEST for $child_1$ will same with PBEST as the *parent*.

F. Search GBEST and PBEST for child₂

For each member of GBEST, the calculated Euclidean distance is measured within each member of the $child_2$. The member of the equation with the smallest NC value will be selected as GBEST to $child_2$. While the value PBEST for $child_2$ will be the same as the parent PBEST.

G. Update Velocity $child_1$ and $child_2$

The equation (12) for update velocity, where $\lambda = sin^3\ \alpha$ and $\alpha = [0, \pi/8]$ related with [3].

$$v_{id,new} = \lambda w v_{id} + c_1 r_1\left(p_{id} - x_{id}\right) + c_2 r_2\left(p_{gd} - x_{id}\right) \quad (12)$$

Description:
$v_{id,new}$ = update velocity
v_{id} = the latest velocity
r_1, r_2 = range value random between (0,1)
p_{id}, p_{gd} = position PBEST and Global BEST
x_{id} = position from particle i, dimension d

H. Update Position $child_1$ and $child_2$

Calculate the latest position of each child using (13).

$$x_{id,new} = x_{id} + \lambda w v_{id} \quad (13)$$

$x_{id,new}$ = update position from particle i

I. Update GBEST

The value of X'_l and X' are not dominated by members in GBEST. The selection process occurs if both the value of the vector (f_1, f_2) of the particles are smaller than the existing members in GBEST. GBEST is updated by adding X'_l and X'_r and by eliminating members of other smaller vector values against X'_l and X'. If the value of X'_l and X'_r are feasible then there is no change in GBEST members.

J. Update Particle

If X'_l is feasible then the particle is updated by comparing the best value among $child_1$ and $child_2$, ($X_i = X'_l$ and $V_i = V'_l$). Furthermore, the new X_i will be compared with the value of P_i and the best will be selected as a P_i with the latest one being the parent, ($P_i = X_i$).

If X'_l is not of worth then there is no renewal of the particle. This condition is repeated from step *E* until step *J*, for all the particles that are generated and the final iteration.

K. Stopping Condition

In the last iteration, each member of the GBEST would be considered optimal in providing solutions to problems. But, for easy understanding and practical solutions, at every change to the actual value of $BK(x)$, $HP(x)$ or other output from ANN using (14).

$$BK(x) = \frac{1}{f_1} \quad \text{and} \quad HP(x) = \frac{1}{f_2} \quad (14)$$

Choose one of the best GBEST members as the optimal solution.

III. RESULT AND DISCUSSION

In this test, there are nine variations in the amount of training data and test data that are used in the training process. The number of iterations that were used in this study was 100 iterations, the value of learning rate was 0.64, 0.4 and momentum values for a total number of hidden layer was 4. Testing results on the variation of training data and testing data are shown in Fig. 4. The graphic on Fig. 4 show that the different combination of training and testing data will produce the variation on MSE. The smallest MSE is obtained at the variation of 90% training data and 10% testing data with the MSE value of 9.9936E-03.

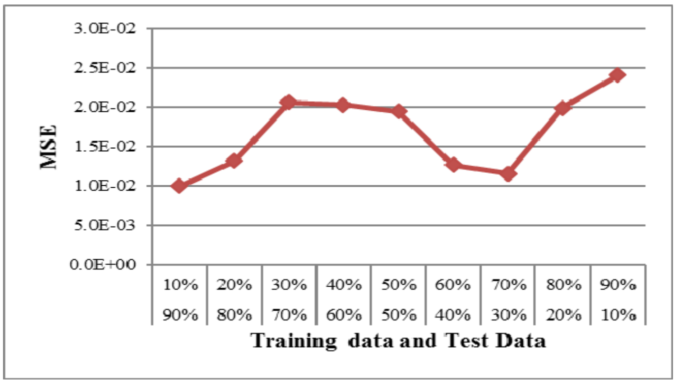

Fig. 4. Testing result of combination training and test data

Fig. 5 show the effect of iteration number to the level of prediction. Variation of the number of iterations performed by a multiple of 100. The MSE produced is also consistent with the range of values on the rate prediction system. Based on the graph of Fig. 5, test results on the variation of total iterations, 100 iterations generates the smallest MSE value to the average value of MSE 9.3458E-03.

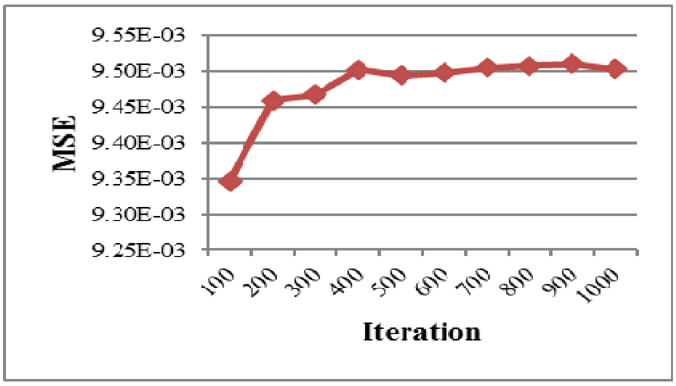

Fig. 5. Testing result of iteration

From the results, the smallest MSE obtained from the number of hidden neuron is 10. A large number of hidden neuron-affecting the system in generating a shift increasingly smaller weights and carefully so that it can obtain the best MSE. A hidden neuron that is tested between 1-10. The result of testing of hidden neuron number is shown in Fig. 6.

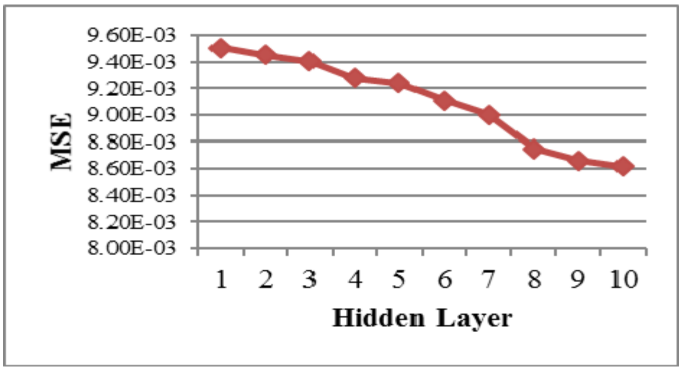

Fig. 6. Testing result of the number of hidden neuron

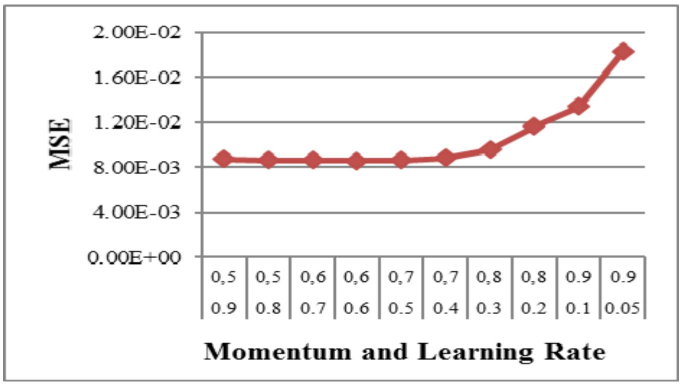

Fig. 7. Testing result of variation of learning rate and momentum

Fig. 7 shows the result of testing on the variation of learning rate and momentum. Based on Fig. 7, the smallest MSE value obtained by the learning rate of 0.6 and momentum of 0.6 is 8.6023E-03. The result of MSE shows the changes occurs with the variation of the value of learning rate and momentum.

IV. CONCLUSION

In this study, testing is done only on the parameters of Backpropagation. The smallest MSE value obtained is 8.6023E-03. This value is obtained by testing using training data of 90%, 10% test data, 100 iterations, the number of hidden layer is 10, learning rate of 0.6 and momentum is 0.6. As for the parameters BIPSO, accordance to the standard PSO. The effect on the plant is optimized BIPSO Dry Weight Plant and Production. The end of GBEST vector value obtained from the effect on plants is 0.222239 and 0.14286. The value of this vector will be changed to actual range value. To obtain crop plants of 4.4964 ton/ha and yield of 6.99985 ton/ha, 0.191 ton/ha or 191 kg/ha of urea, 0.201 ton/ha or 201 kg/ha of SP36, 0.288 ton/ha or 288 kg/ha of KCL and 48.3 ton/ha of Biochar are needed. From the results obtained, the optimization of fertilizer on maize crops is capable to give the prediction results and optimization solutions on plants as compared to the research conducted directly on the field.

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