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A network that really works – the application of artificial neural networks to improve yield predictions and nitrogen management in Western Australia

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Abstract

Yield predictions are notorious for being difficult due to many interdependent factors such as rainfall, soil properties, plant health, plant density etc. This study is based upon the author's previously published work and extends its findings by further investigating the best mathematical solution to this dilemma. Artificial intelligence (AI) techniques have been applied to a large set of soil, plant, rainfall, and yield data from CSBP's field research trial program. Here we further differentiate by investigate two ANN techniques, a genetic algorithm with back propagation neural networks (GA-BP-NN) and a particle swarm optimization with back propagation neural networks (PSO-BP-NN). Results indicate that the GA-BP-NN technique offers a slightly better yield correlation. Our main conclusion is that this method would offer growers more confidence in making a better nitrogen decision during the season than currently available models due to more precise yield predictions. It also can also contribute to possibly better grain marketing decisions later in the season.

Key Words: artificial neural networks, yield, nitrogen management

Introduction

Western Australia (WA) produces currently more than 40 percent of the national wheat crop. However, broad-acre soils in WA are inherently low in soil mineral nitrogen (N) and organic N and thus N is required to lift production on these soils. Management decision tools for N applications are available, but are lacking accuracy to predict N requirements often as a result of inaccurate yield predictions.

Yield predictions are based on many interdependent factors such as rainfall, soil properties, plant health, plant density etc. Those factors are dynamic. One of those important factors is i.e. soil nitrogen, which can change in its plant available amount quickly during the season. The additional problem is that growers want to know about their yield forecasts as early as possible to gauge crop N demand and yield responsiveness to N fertiliser.

Traditional data modelling techniques have been worked into N decision support systems (DSS) for a long time in WA. They do require continuous research and expertise to develop and maintain the underlying quantitative cause-effect relationships. Recently AI applications that mimic our brain capability to learn have found their way into DSS and offer a more flexible alternative approach for easier, more cost-effective maintenance without compromising the quality of the decision support. Soil moisture data, for example, has been estimated successfully for irrigation scheduling using ANN in paddy fields in West Java,

Indonesia (Arif et al., 2012). Furthermore, an ANN technique has been applied to predict longan yields with an average of 80-83% accuracy in northern Thailand and was then incorporated into a mapping program, ArcMap (Thongboonnak and Sarapirome, 2011). ANN could be applied to a wide range of different agricultural DSS. This study examines two ANN techniques for yield predictions of wheat in WA using local soil, plant and rainfall data.

In dryland agriculture, rainfall is usually one of the most yield limiting factors. It also determines N mineralisation and N availability. Rainfall in this Mediterranean type climate is not only variable in its intensity, but it is also geographically and temporally highly variable. This affects the N cycle and hence the yield predictions and N status will have to be based on such input factors. Figure 1 of the south-west in WA demonstrates the seasonal difference of the effect of summer rainfall on soil nitrate values due to N mineralisation in 2013 (left, with summer rain) compared with 2014 (right, no or little summer rain). Images are obtained from more than 50,000 topsoil samples for each map.

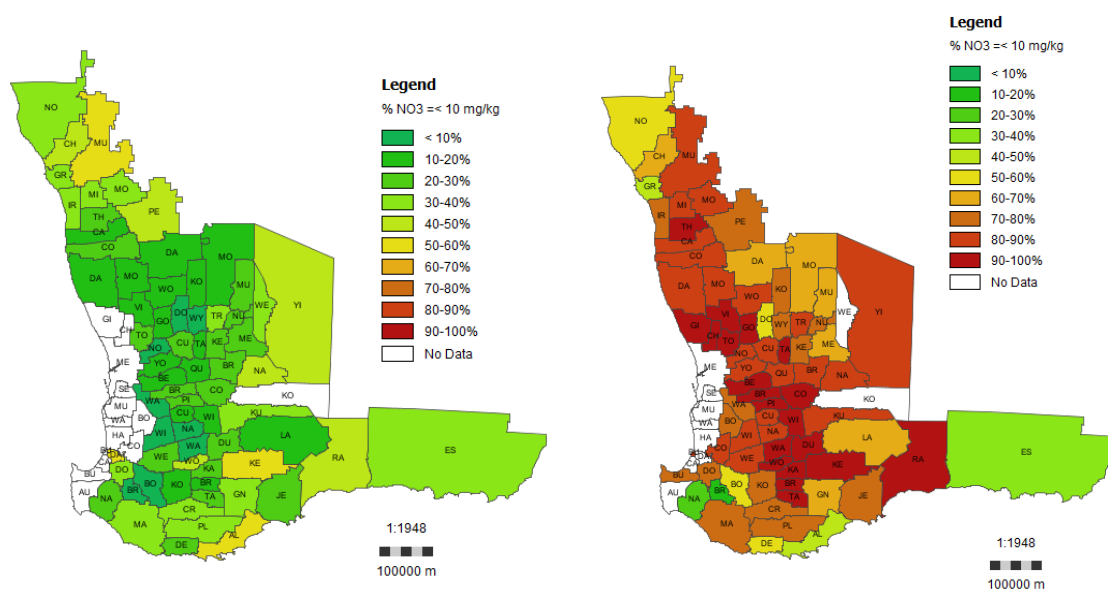


Figure 1: Seasonal difference in nitrate values at the start of the 2013 season (left) compared with the 2014 season (right).

In this study, yield predictions are derived from multi-factorial relationships. The relationships have been captured in the matrixes of different ANN techniques that have been applied. Furthermore, the importance of each factor on yield has been statistically tested to understand the main forces behind yield predictions.

Material and Properties

CSBP field trial data has been used to compile the database. The sample size comprises of 522 data points and variables of those 24 N responsive field trials include summer and growing season rainfall, cultivar, soil texture, location, soil organic carbon (%), soil pH_{CaCl2}, previous crop in rotation, sowing and emergence date, sampling date for plant tissue analysis, plant N (%), plant NO₃ (mg/kg), shoot dry weights and biomass. For a more detailed

description of the data see Neuhaus et al. (2014). Initially this dataset for testing and validating has been determined using a principal component and cluster analysis. The workflow for yield predictions followed a 2 step process in which firstly the N status was estimated from soil and plant data and secondly this N status combined with rainfall and biomass data estimated yield.

As a first statistical analysis, a principle component analysis (PCA) was conducted on the data to investigate the importance of management factors on yield. Secondly, a cluster analysis was performed to identify pattern in the data.

The principle component biplot in Figure 2 shows principle component 1 (PC1) versus principle component 2 (PC2), describing the principal component loadings which represent the traits used to explain the yield variance for each dimension (ie for horizontal axis, PC1 shows that N%, NO₃, plant age, and above-ground plant dry weight explain the majority of the 24.6% in this dimension). After adjustment for these traits (ie PC1), PC2 shows that the largest components are pH_{CaCl2}, seeding rate, the previous crop and emergence day, which explain a further 20.1% yield variance. Thus plant vigour is a more important trait than the other traits of selected management conditions.

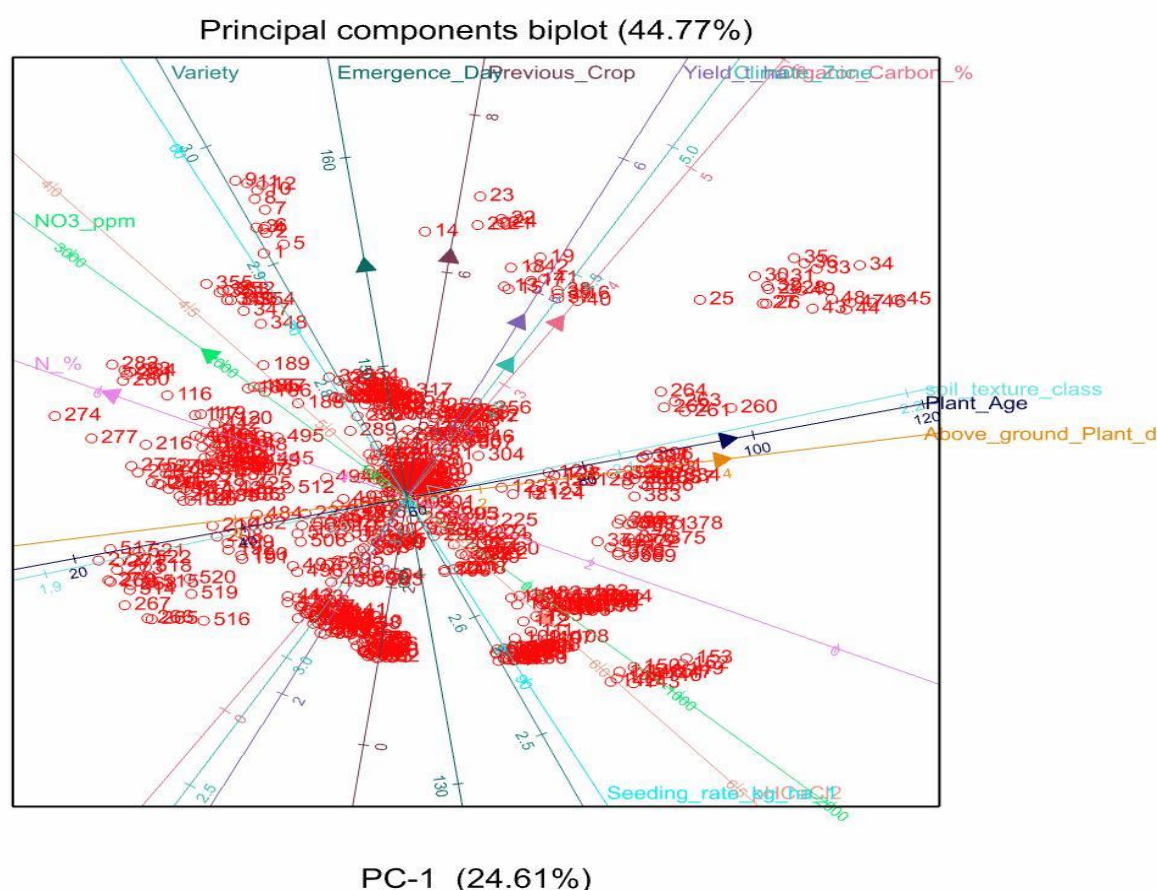


Figure 2: PCA of yield related management factors.

The cluster analysis showed the highest weights for soil organic carbon (%), which was 1.39, soil pH_{CaCl2}, which was 0.41 and location, which was 0.39. Soil organic carbon, soil pH_{CaCl2} and location (climate) affect N mineralisation and therefore it is not surprising to observe this pattern.

Methods

The back-propagation neural network (BPNN) includes input layer, hidden layer(s), and output layer, as shown in Figure 3.

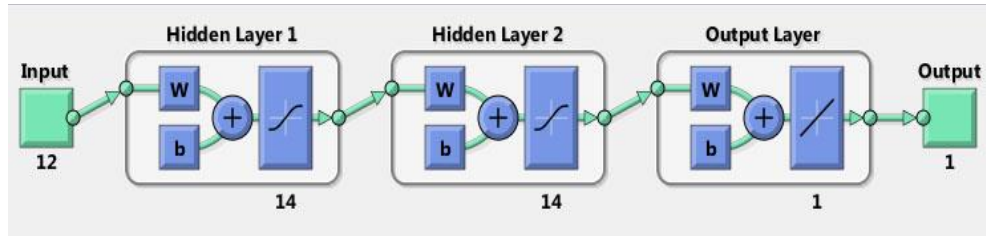


Figure 3: The structure of BPNNs

The number of nodes in each hidden layer is computed as:

$$S = \text{round}(\sqrt{\text{inputnum} + \text{outputnum}}) + 10$$

where *inputnum* is the number of inputs (features), and *outputnum* is the number of output.

In Figure 3, we can find the structure of BPNNs includes two hidden layers and each hidden layer has 14 nodes.

The basic BPNNs algorithm adjusts the weights in the steepest descent direction (negative of the gradient). Although the function decreases most rapidly along the negative of the gradient, it may not produce the fastest convergence, so the steepest descent is often slow in convergence. To overcome these drawbacks, the conjugate gradient algorithm is employed to search along conjugate direction, so as to produce generally faster convergence than steepest descent one.

As indicated above, the performance of the BPNNs algorithm is very sensitive to the proper setting of the initial weights and parameters. In general, the weights of BPNNs are initialized through a random process, which means the performance and output could be different from each running the algorithms. So it is of great importance to obtain the ‘best’ performance by choosing the optimal initial weights of BPNNs.

The task of BPNNs is to be divided into two steps: 1). Find the optimal weights of BPNNs; 2). Build the BPNNs model for yield predictions and nitrogen management.

Due to the inherent nature of complexity, it is almost impossible to find the optimal weights of BPNNs using the traditional analytic methods. In this work, two techniques are employed and implemented to optimize the initial weights of BPNNs, i.e., particle swarm optimization (PSO) and genetic algorithms (GA). Both PSO and GA are able to evolve with some randomness towards optimal solutions.

PSO (Kennedy and Eberhart, 1995) is one of swarm intelligence (SI) techniques, including ant colony system (Dorigo and Gambardella, 1997), artificial bee colony algorithm

(Karaboga and Dervis, 2010), etc. PSO is an optimal computation technique by mimicking the behaviour of bird flocking. In PSO algorithm, each particle represents a potential solution, and is linked to a certain degree of fitness that is determined by a fitness function. The position and velocity of each particle are changing to the better solution over time by estimating its fitness.

In a D-dimensional space, the group that consists of n particles can be represented as $X = (X_1, X_2, \dots, X_n)$, and the i -th particle has a D-dimensional vector $X_i = (X_{i1}, X_{i2}, \dots, X_{iD})$ that represents a potential solution. The velocity of each particle in each dimension is defined as $V_i = (v_{i1}, v_{i2}, \dots, v_{iD})$, the best position values of individual and group are represented as $P_i = (p_{i1}, p_{i2}, \dots, p_{iD})$ and $P_g = (pg_1, pg_2, \dots, pg_D)$. The velocity and position are updated in terms of the best values of individual particle and group, defined as:

$$V_{id}^{(t+1)} = \omega \times V_{id}^{(t)} + U[0,1] \times \psi_1 \times (p_{id}^{(t)} - x_{id}^{(t)}) + U[0,1] \times \psi_2 \times (p_{gd}^{(t)} - x_{id}^{(t)}) \quad (1)$$

$$X_{id}^{(t+1)} = X_{id}^{(t)} + V_{id}^{(t+1)} \quad (2)$$

where $U[0,1]$ samples a uniform random distribution, t is a relative time index, ψ_1 and ψ_2 are weights trading off the impact of the local best and global best solutions' on the particle's total velocity.

GA searches for the optimal solution in a different way. As indicated in Figure 4, GA finds the optimal solution in an iterative manner:

1. Initialize a population of candidate solutions;
2. Evaluate each individual in the population with the fitness function.
3. The individuals are evolved through the following process:
 - Elitist selection;
 - Crossover;
 - Mutation.
4. Check the termination condition(s):
 - Terminate if the stopping criteria are met;
 - Otherwise, generate a new population, and go back to step 2.

During the evolution, the best solution in the population is always retained in next population. So this strategy can guarantee the convergence of the GA algorithms.

Results

The ‘optimal’ weights of BPNNs can be obtained, with PSO or GA techniques. The related fitness curves of PSO and GA are plotted as below:

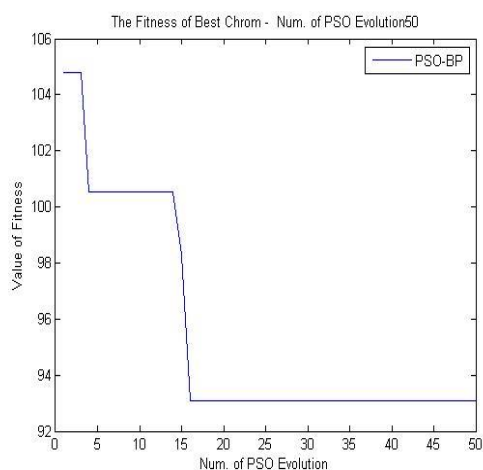


Figure 4: Fitness Diagram of PSO-BPNNs

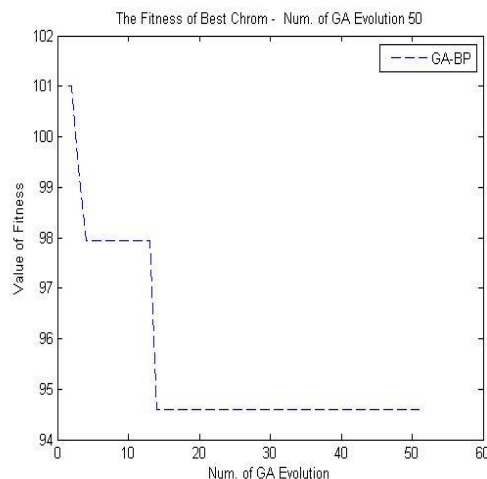


Figure 5: Fitness Diagram of GA-BPNNs

From the diagrams in Figure 4 and 5, it is clear either PSO or GA is able to converge to ‘optimal’ fitness in about 20 iterations.

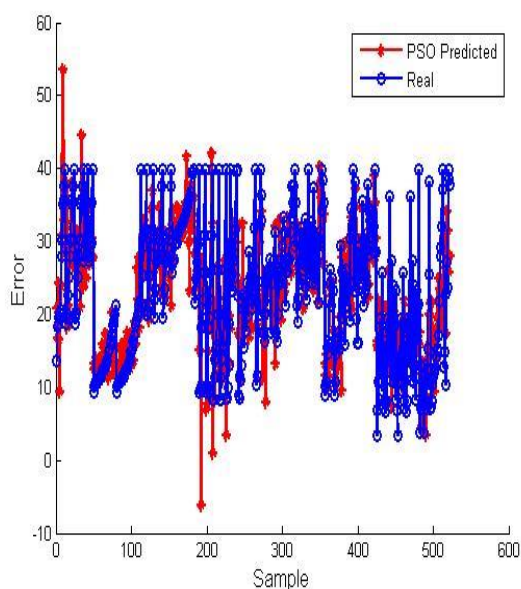


Figure 6: PSO-BPNNs for N status data

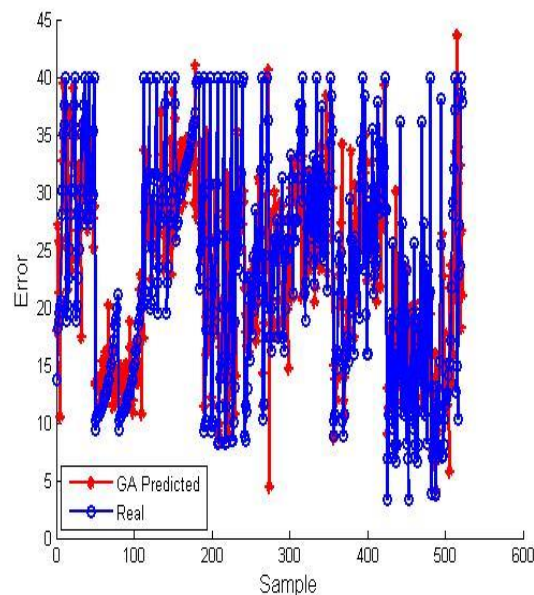


Figure 7: GA-BPNNs for N status data

For predicting the outputs of the N status with PSO-BPNNs, the prediction errors are plotted in Figure 6, the mean squared error (MSE) is 7.0882, and the correlation coefficient is 0.6775. For predicting the same outputs with GA-BPNNs, the prediction errors are plotted in Fig. 7, the mean squared error (MSE) is 7.1356, and the correlation coefficient is 0.6718.

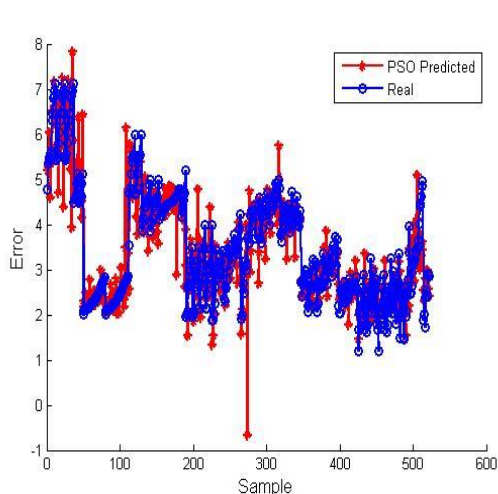


Figure 8: PSO-BPNNs for yield data

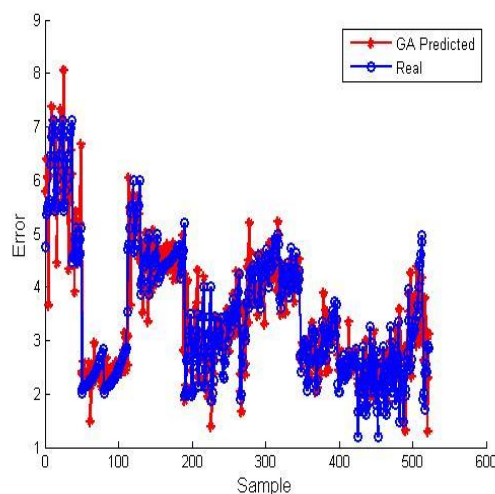


Figure 9: GA-BPNNs for yield data

For predicting the yield outputs with PSO-BPNNs, the prediction errors are plotted in Figure 8, the mean squared error (MSE) is 0.6103, and the correlation coefficient is 0.8772. For predicting the same yield outputs with GA-BPNNs, the prediction errors are plotted in Figure 9, the mean squared error (MSE) is 0.5359, and the correlation coefficient is 0.9043.

The difference in correlation factors from the dataset for the N status ($r^2 = 0.67$) and the dataset for yield ($r^2 = 0.88$ and 0.90) reflects the sensitivity of yield predictions to rainfall and biomass as the overriding and dominant factors. Rainfall is not manageable by the grower, but biomass is to some extent, although it depends largely on rainfall too.

Discussion

This study found statistically significant yield correlations using back propagation neural networks and thereby agrees with other AI studies which also found highly significant yield predictions, such as findings from Panda et al. (2010) and Thongboonnak and Sarapirome (2011). In this study, the GA-BP-NN has produced reliable and slightly better correlations than the PSO-BP-NN method. Furthermore, this study complements earlier work which showed that an artificial neural network (ANN) using the “Leave Out One Cross Validation (LOOCV)” technique is an accurate technique to forecast yield with optimum N versus growers yield at the time of plant sampling with no further N applications (Neuhaus et al.,

2014). Yield predictions were about 30% more accurate than expert models such as APSIM/Yield Prophet that draw on traditional modelling techniques.

French and Schultz (1984) emphasised the importance of rainfall for yield predictions in wheat grown a Mediterranean-type climate. Oliver et al. (2009) added some simple modifications like for example soil texture to adjust the rainfall data for yield predictions. However, even with those adjustments the correlation is well below the yield correlation from the GA-BP-NN used in this study. The better correlation from the GA-BP-NN method may be contributed to either the computational method and/or the inclusion of plant testing data.

Conclusion

It can be concluded from this study that the GA-BP-NN method, if available as a decision tool in WA, would improve N management during the season and thereby the profitability and sustainability of N inputs into the farming system. It also can also contribute to possibly better grain marketing decisions later in the season.

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