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Modelling of Energy Consumption in Wheat Production Using Neural Networks

"Case Study in Canterbury Province, New Zealand"

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Abstract**—**An artificial neural network (ANN) approach was used to model the energy consumption of wheat production. This study was conducted over 35,300 hectares of irrigated and dry land wheat fields in Canterbury in the 2007-2008 harvest year.

In this study several direct and indirect factors have been used to create an artificial neural networks model to predict energy use in wheat production. The final model can predict energy consumption by using farm condition (size of wheat area and number paddocks), farmers' social properties (education), and energy inputs (N and P use, fungicide consumption, seed consumption, and irrigation frequency), it can also predict energy use in Canterbury wheat farms with error margin of ±7% (± 1600 MJ/ha).

Keywords**—**Artificial Neural Network, Canterbury, Energy consumption, Modelling, New Zealand, Wheat

I.INTRODUCTION

NEW ZEALAND is one of the countries with the highest energy input per unit (in agriculture) in the world. Furthermore, in terms of shipping, the influence of increasing fuel costs in the world is greater on New Zealand farming than in other countries.

This study was conducted over 35,300 hectares of irrigated and dry land wheat fields in Canterbury, New Zealand, in the 2007-2008 harvest year, which reported 87% of the wheat area and 66% of arable area harvested in New Zealand.

Using energy in developed and developing countries have created several environmental, commercial, technical, and even social sciences, which need to study. Analysing numerous amount of different sorts of information is necessary to reduce the energy consumption and its environmental impacts. Some of the energy sources in agriculture sector are classified in other sectors. For example, fuel consumption in farm operations may be classified in the transport sector or indirect energy sources (fertilizers, seeds, and agrichemicals) may be estimated in the industrial sector. Consequently, official national statistics usually do not show accurate energy use in agriculture and they pay very little attention to the energy consumption of agriculture sector [1].

Energy modelling is an interesting subject among engineers and scientists who are concerned about energy production and consumption and environmental impacts [2, 3]. In energy area, a wide range of models have been used, from geological models in research on natural resources, to modelling future energy demand [3].

In the past, regression analysis was the common modelling technique on energy studies. However, recently, neural networks (NN) have been increasingly used in energy studies [4]. Due to ability of neural networks to model complex nonlinear systems in a flexible and adaptive manner, NN have been used more and more in the recent years [5]. Several studies have used NN for classification, prediction, and problem solving in energy field. NNs have been applied by researchers in a wide range of application areas, such as mathematics, engineering, medicine, economics, environment, and agriculture [4]. Numerous number of researchers have applied neural networks in the modelling of various scenarios to solve different problems, in which no explicit formulations were available [6]. The main advantage of neural networks is that they are able to use prior information (historical underlying process data). In most studies, a feed-forward Multi-Layered Perception (MLP) paradigm trained by back propagation (BP) is used. Due to its documented ability to model any function, MLP trained with BP is selected to develop apparatus, processes, and product prediction models [5, 7, 8].

In the last twenty years, use of neural networks in energy studies has increased and a wide range of studies using neural networks (NNs) in energy systems has been done [9]. Javeed Nizami and Ahmed G. Al-Garni [10] applied seven years of data to develop a two layered artificial neural network forecasting model to relate the electric energy consumption in the Saudi Arabia to the weather data, global radiation, and population. A neural network was developed by Mohandes et al. [11] to predict the wind speed prediction. Kalogirou and Bojic [12] developed and applied a multilayer back propagation learning algorithm to predict energy consumption of a passive solar building. Kalogirou [13] has reviewed various applications of NNs in energy studies. Fang [6] developed a neural networks model to estimate energy requirements for the reduction of cultivated wheat area. Aydinalp [14] used a simple neural network based energy consumption model for the Canadian residential sector. An artificial neural network model to predict the regional peak load of electricity in Taiwan has been used by Hsu [15].

The benefits of using NN models are the simplicity of application and robustness in results. The application of ANNs has developed into a powerful tool that can approximate any nonlinear input-output mapping faction to any degree of accuracy in an iterative manner. ANNs have many attractive properties for the modelling of complex production systems, universal function approximation capability, resistance to noisy or missing data, accommodation of multiple non-linear variables with unknown interactions, and good generalization ability [16].

In the processing of inputs by network, each neuron processes the weighted inputs through a transfer function to produce its output. The function may be a linear or a nonlinear function. There are several transfer function, such as Logistic, Hyperbolic-tangent, Gussian, and Sin. The output depends on the particular function. This output is then sent to the neuron in the next layer through weighted corrections

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and these neurons complete their outputs by processing the sum of weighted inputs through their transfer functions. When this layer is the output layer neuron output is the predicted output.

Several methods of error estimation have been proposed. The Mean square error (MSE) is the most commonly used error indicator of the prediction over all the training patterns. MSE is a very useful to compare different models; it shows the networks ability to predict the correct output. The MSE can be written as:

$$MSE = \frac{1}{2N}\sum_{i}^{N}(t_i - z_i)^2$$

where ti and zi are the actual and the predicted output for the ith training pattern, and N is the total number of training patterns [17].

Accuracy of data set is very important because mistaken inputs or outputs change the model or increases the error [9, 17]. Also, in neural networks, it is necessary to use numeric data. In non-numeric data, such as ID numbers, the numbers do not have any order or relevance; therefore, weights can not create the correct and proper interaction between inputs and outputs. To solve this limitation, transferring qualitative data to quantitative data through meaningful classification is a common way. Moreover, in neural network training, a range of inputs and data are used; consequently, if the data focuses only on a limited range or some input factors are not incorporated, the model will not be powerful [9].

When the number of variables is notably high, especially when there are limited number of samples, data reduction is useful. The best common method for data reduction is principle component analysis (PCA). PCA is a useful method to select the most important uncorrelated variables. PCA uses the mean and variance of each input variable and the covariance between variables to create a covariance matrix (COV) [17].

When some input variables correlate with one another, another problem that is called multicollinearity, will appear. Correlation between inputs reduces the chance of having a unique solution [17]. Furthermore, it is better to solve any problem with the minimum number of variables.

II. METHODOLOGY

Energy consumption is defined as the energy used for the production of wheat until it leaves the farm. The data was collected from three different sources: questionnaire, literature review, and field measurements. The energy inputs estimated in this study are those that go into on-farm production systems before the post-harvest processes. The study has considered only the energy used in wheat production, without taking into account the environmental sources of energy (radiation, wind, rain, etc).

In this study, energy consumption in wheat production was analysed based on direct energy sources and indirect energy sources including human, fuel, fertilizers, pesticides, machinery, and seed.

The total energy input (E) is determined from the sum of the amount of input factors (A_i) multiplied by appropriate energy conversion coefficients for that factor (C_i).

$$E = \Sigma(A_i\, C_i)$$

For converting farm inputs and outputs to energy there are different energy conversion coefficients. In this study, energy conversion coefficients were investigated and selected carefully. More than direct and indirect energy inputs, there are other different factors, such as technical, social, geographical, and financial factors, which may influence energy consumption indirectly. The wide range of factors, such as farmers, social properties, age of tractor and equipment, power of tractor, number and size of paddocks, and yield were studied. These indirect factors and energy inputs were examined to design the model to predict energy consumption in wheat production. Involving indirect factors in energy prediction may help to reduce energy consumption and environmental impacts with minimum cost and minimum farmers' income reduction.

ANNs can be successfully trained to describe the influence of energy sources, agricultural operation, and indirect properties on energy consumption in wheat production. The number of input patterns used in this study was 40, which was selected from farms. Initially 30 samples were randomly selected for training, and the remaining 10 samples were used for validation. To avoid the nonuniqueness of solution, correlation of inputs were examined and correlated data removed. Since then, the number of inputs was reduced by using PCA. Preliminary trials indicated that two hidden layer networks gave better results than one hidden layer networks.

After several exercise, a modular neural network with two hidden layers was selected. In modular network structure, model characterize by a series of independent neural networks after input layer, which operate on separate inputs to achieve some subtask of the task of the network, expects to perform.

The Quick Prop method was used as the learning method; because, it is a fast training method to reduce error and finding best model. Quick Prop implicitly uses second derivative of error to adjust weights. In the each iteration of the Quick Prop, the update for the weights and biases was regulated as follows:

$$w_{m+1} = w_m + \Delta w_m$$

$$\Delta w_m = \frac{d_m}{d_{m-1} - d_m}\Delta w_{m-1}$$

$$d_m = \sum_{n-1}^{N}\left[\frac{\partial E}{\partial w_m}\right]_n$$

where Δw_m is the current weight, d_m is derivative for the current epoch m; and $\partial E_m/\partial w_m$ is the current error gradient [17].

Different functions, such as hyperbolic tangent (tanh) sigmoid, logistic sigmoid, Gauss Bell, linear, and Sine were tested and in final model tanh sigmoid function was selected for input layer and first hidden layer and logistic sigmoid function was applied for second hidden layer of the general form:

$$L(u) = [1 + e^{-u}]^{-1}$$

$$\tanh(u) = \frac{1 + e^{-u}}{1 - e^{-u}}$$

where $L(u)$ is logistic sigmoid function; $\tanh(u)$ is hyperbolic tangent sigmoid function; and u is input [17].

It is important to note that various combinations of number of layers and number of neurons, and different functions, structures, and learning methods were examined to find best model with minimum iteration. Number of neurons and number of inputs and outputs were optimized through using genetic algorithm

III. RESULTS

On Average, energy consumption in wheat production in Canterbury was about 22,566 MJ/ha as shown in Table 1; of this, 36% was direct energy in form of diesel at 3,121 MJ/ha and electricity at 4,870 MJ/ha. Fertilizer is ranked first with 47% (10,651 MJ/ha) and electricity is ranked second with 22% (4,870 MJ/ha). Table 2 presents the amount and percentage of energy sources consumption in wheat production. It appears that fertilisers, especially urea, were the most important factor of energy sources in wheat production.

TABLE I PROPERTIES OF ENERGY CONSUMPTION (MJ/ha)

	Mean	*Max*	*Min*	*SD*	95% confidence interval	
					Lower	*Lower*
MJ/ha	22,566	36,230	11,497	6,125	20,608	24,524

TABLE II ENERGY SOURCES IN WHEAT PRODUCTION (MJ/ha)

	Human	*Seed*	*Fertilizer*	*Pesticide*	*Electricity*	*Machinery*	*Fuel*	*Total*
MJ/ha	6	1,266	10,651	911	4,870	1,741	3,121	22,566
%	0.03	6	47	4	22	8	14	100

After data reduction process, eight variables were selected including wheat area (ha), farmer's education, nitrogen consumption (kg), phosphate consumption (kg), fungicide consumption (kg), seed amount (kg), irrigation frequency, and number of paddocks. These variables are not correlated and they were selected by using PCA. Estimating all variables are easy and farmers have clear ideas about them. Consequently, the final model can predict energy use with minimum estimation error.

After testing different gradient decent, functions, and structures, a modular network with two hidden layers were developed as shown in Figure 1. Number of neurons, inputs and outputs of each layer were optimized by using genetic algorithm optimizer. The ANN model after 1100 iteration achieved the best result with scaled MSE= 2.74 E-2. The MSE of final ANN model was estimated 519,344.

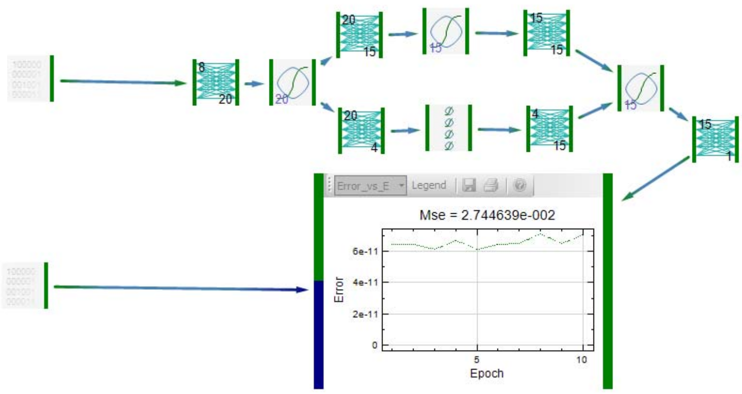

Fig. 1 Structure of modular network and number of inputs and outputs of each layer

Estimation of energy consumption by the NN accounted for 98% of actual energy use variability (Fig 2). Regression between observed versus predicted energy consumption is very high and slope equal to 0.95.

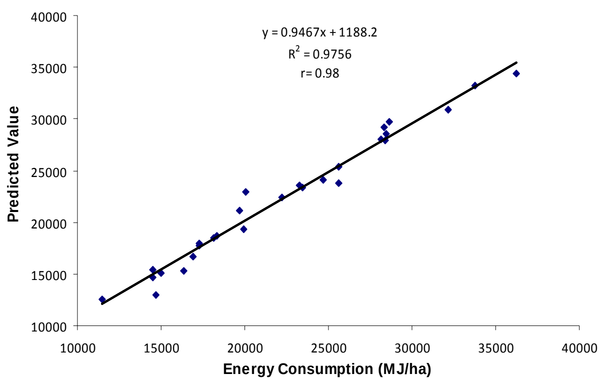

Fig. 2 Relationships between observed and predicted fuel consumption (Training) in ANN model

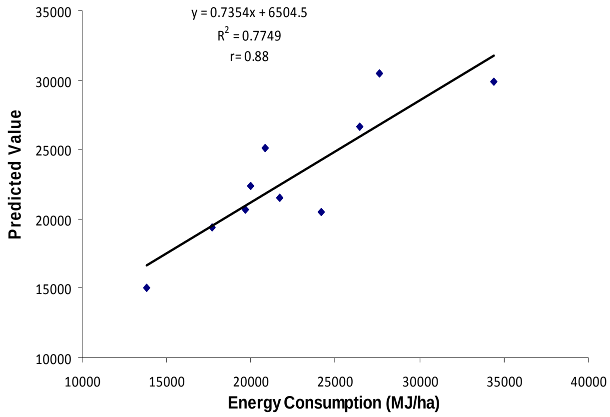

Fig. 3 Relationships between actual and predicted fuel consumption (Validation) in ANN model

As shown in Figure 4, the final training model predicted energy consumption around ±1680 MJ/ha. As discussed before, in agricultural production, there are several uncontrolled factors, which would influence energy consumption in crop production; therefore, the result of this study is tremendously interesting and the final model can predict energy use in wheat production with minimum expected error. It is noticeable that some of the variables in the final model are not changeable, and they show the farming condition. For example, number of paddocks and fungicide consumption would affect on energy consumption indirectly. Therefore, the next step (in future studies) should be exploring the links between input variables and energy consumption in agricultural production.

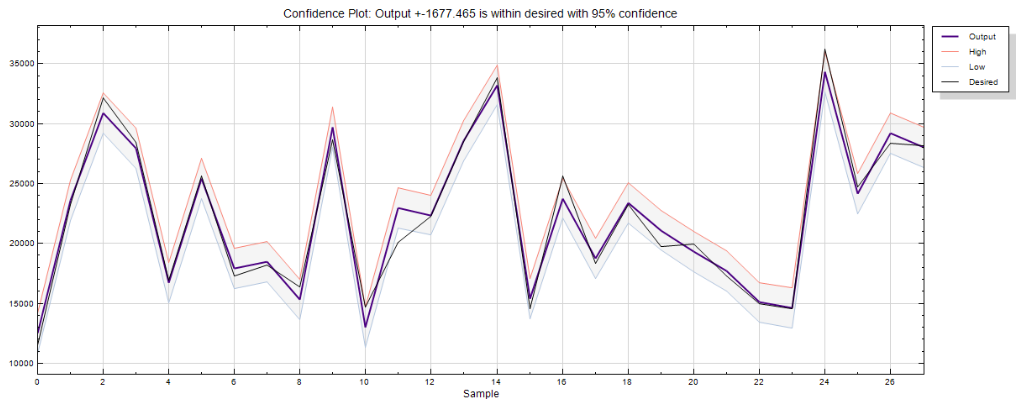

Fig. 4 Predicted, observed, and the 95% Confidence Interval for the fuel consumption based on the artificial neural networks model (training data)

IV. Conclusion

In this study, for the first time an ANN model was designed to predict energy consumption in agricultural production. Additionally, due study is the first to include several indirect factors, such as social properties and farm conditions. The final model can predict energy consumption by using farm condition (size of wheat area and number of paddocks), farmers' social properties (education), and energy inputs (N and P use, fungicide consumption, seed consumption, and irrigation frequency). It can also predict energy use in Canterbury arable farms with error margin of ±7% (± 1600 MJ/ha). This size of error in agricultural studies with several uncontrolled factors is fascinating.

The result of this study shows the ANN model ability to predict energy consumption in wheat production by using different heterogeneous data. Using dissimilar variables, such as farm conditions and social factors would improve the ability of decision makers to look at the problems from different aspects. Given the findings of this study, the most significant areas for improving overall modelling energy are as follows:

- Developing the model, to estimate energy use of whole products of each farm to find the most energy efficient combination of different agricultural production under different conditions. To develop this complex model, several farms must be involved and their production and operation should be investigated carefully.

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- Using the same methodology to create similar model to predict fuel consumption, CO_2 emission, and wheat and other agricultural production. It is possible to use the same database for these investigations. Modelling the above factors and energy consumption by using social and technical parameters would open new doors to science.

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