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INFERENTIAL NEURAL SYSTEM TO CONTROL THE FLUID FERTILIZER APPLICATION

José A. C. Ulson[†], Sérgio H. Benez[‡], Ivan N. da Silva[†], André N. de Souza[†]

[†] *University of São Paulo – UNESP*
Department of Electrical Engineering
CP 473, CEP 170133-360
Bauru – SP, Brazil

[‡] *University of São Paulo – UNESP*
Department of Agricultural Engineering
CP 237, CEP18603-970
Botucatu – SP, Brazil

Abstract: The application process of fluid fertilizers through variable rates implemented by classical techniques needs a flow meter in the primary controlled variable. This paper proposes an inferential control system based on Artificial Neural Network of the type multilayer *perceptron* for the identification and control the fertilizer flow rate. In this approach, there is no flow meter since the control is made through secondary variables. The neural network training is made by the algorithm of *Levenberg-Marquardt* with training data obtained from measurements. The results indicate a fast, stable and low cost control system for precision farming. *Copyright © 2002 IFAC*

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1. INTRODUCTION

The application of fertilizers in a precise way along the field is of fundamental importance, in as much as it involves biotics, abiotics, social and economics aspects.

According to the principles of the precision farm, the need of nutrients for a certain cultivation varies over the area and along the deepness of the soil (spatial variability). Thus, the rational use of the fertilizers is obtained when its application obeys the real necessity of each portion of the soil.

For a typical Brazilian sugar cane grower, the costs involved with fertilizers represent approximately one fourth of the production expenses. Therefore, the effective management of these costs has had a significant impact on the eventual profit obtained from crop production processes. Besides, it is well known that so much the deficiency as the excess of nutrients can reduce productivity and affect the crop quality. For instance, the excess of nitrogen (N) in the soil can increase the vegetative growth, however, it can reduce the sucrose content in sugar beets and leave them more tender, turning the more exposed to the attack of plagues (Morgan and Ess, 1997). This excesses that leach through the soil often ends up in groundwater wells, streams and lakes - the same resource that provides water for most of the world population.

In this scenario, the equipments used for fertilizers application should have some control systems that can change the fertilizer application rate in accordance with the real necessity of the cultivation. But, this affirmation doesn't represent the reality because the equipments for fluid fertilizer variable application rate had have high cost for the most of Brazilian's farmers and small enterprises. Even so, the fluid fertilizer application over the field are still made through average rate.

This work describes a new inferential control system based on Artificial Neural Networks (ANN) destined to control the application of nitrogen (N), phosphorus

(P) and potassium (K) without necessity of flow meter devices. More specifically, it is used neural nets of the type multilayer *perceptrons* (MLP) (Haykin, 1999; Kosko, 1992) for the identification and control of the fertilizer application system, using indirect measurements like tank level, centrifugal speed pump, and others variables and parameters that are related to the fertilizer flow through the applicator system. The network training is made by the algorithm of Levenberg-Marquardt (Hagan and Menhaj, 1994) with training data obtained from workbench measurements.

For this purpose, the organisation of the present paper is as follows. In Section 2, the basic aspects relative to systems identification and artificial neural networks are described. In Section 3, a review of the fertilizer application systems is presented. In Section 4, the control strategy used to the fertilizer application system is formulated. In Section 5, results are included to validate the proposed methodology. In Section 6, the key issues raised in the paper and the conclusions drawn are presented .

2. SYSTEMS IDENTIFICATION AND ARTIFICIAL NEURAL NETWORKS

In this context, a system identification technique is used to simplify the system control and make its implementation cheaper than conventional techniques. In this problem, some identification method *P(w)* with a convenient algorithm (in this case an Artificial Neural Network – ANN), finds the best parameterization that represents the dynamic of the process, as shown in Figure 1. The parameterization is tuned through the minimization of reconstruction error obtained from the output *e(k)*, which it is used to adjust the ANN weights (Hagan, 1999).

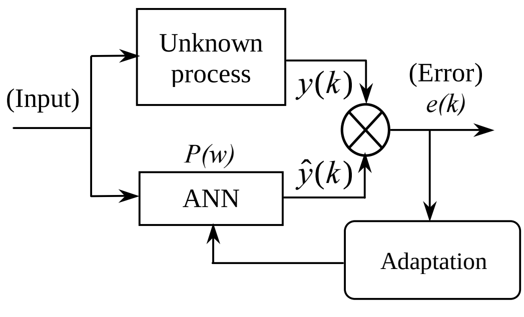

Fig. 1. Identification system with an ANN

In this paper, artificial neural networks of the type perceptron has been used to identify the process and to control the fertilizers application rate.

The ability of Artificial Neural Networks in mapping functional relationships has become them an attractive approach that can be used in several types of problem (Haykin, 1999). This characteristic is particularly important when the relationship among the process variables is non-linear and/or not well defined, and thus difficult to model by conventional techniques.

An artificial neural network is a dynamic system that consists of highly interconnected and parallel non-linear processing elements that shows extreme efficiency in computation. The main benefits of using ANN on the control system of fluid fertilizer application are the following: i) the ability of learning and therefore generalisation; ii) the facility of implementation in hardware; iii) the capacity of mapping complex systems without necessity of knowing the eventual mathematical models associated with them; and iv) the possibility of reducing the costs involved with the crop production processes.

A typical feedforward ANN is depicted in Figure 2, with m inputs and p outputs, where each circle represents a single neuron. The name feedforward implies that the flow is one way and there are not feedback paths between neurons. The output of each neuron from one layer is an input to each neuron of the next layer. The initial layer where the inputs come into the ANN is called the input layer, and the last layer, i.e., where the outputs come out of the ANN, is denoted as the output layer. All other layers between them are called hidden layer.

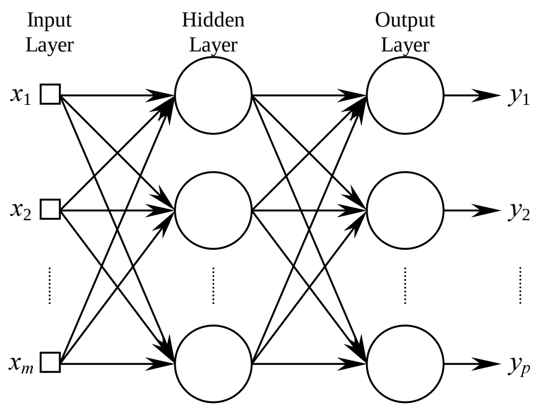

Fig. 2. Typical feedforward ANN

Each neuron can be modelled as shown in Figure 3, with *n* being the number of inputs to the neuron.

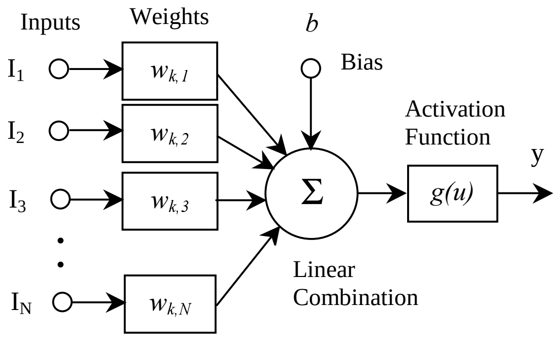

Fig. 3. Single artificial neuron

Associated with each of the n inputs x_i is some adjustable scalar weight, w_i (i=1,2,…,n), which multiplies that input. In addition, an adjustable bias value, b, can be added to the summed-scaled inputs. These combined inputs are then fed into an activation function, which produces the output y of the neuron, that is:

$$y = g(\sum_{i=1}^{n} w_i x_i + b) \qquad (1)$$

where g is a sigmoid function defined by $g(u)=(1+e^{-u})^{-1}$.

The training process of the neural network consists of the successive presentations of input-output data pairs. The basic structure having one hidden layer has been shown to be powerful enough to produce an arbitrary mapping among variables. During the training, the data are propagated forward through the network, which adjusts its internal weights to minimise the function cost (weighted squared deviation between the true output and the output produced by the network) by using the back-propagation technique. The details of the derivation of the back-propagation algorithm are well known in literature and its steps can be found in (Haykin, 1999). A review of the main steps of the algorithm is presented here. The function to be minimised is the sum of the average squared error (E_{AV}) of the output vector,

$$E_{AV} = \frac{1}{N}\sum_{k=1}^{N} E(k) \qquad (2)$$

where N is the number of training points and $E(k)$ is the sum of squared errors at all nodes in the output layer, i.e.,

$$E(k) = \frac{1}{2}\sum_{j=1}^{p} (d_j(k) - y_j(k))^2 \qquad (3)$$

For an optimum weight configuration, $E(k)$ is minimised with respect to the synaptic weight w, so that for each data set,

$$\frac{\partial E(k)}{\partial w_{ji}^{l}} = 0 \qquad (4)$$

where w is the weight connecting the neuron j of the l-layer to neuron i of the $(l-1)$-layer.

Finally, the weights of the network are updated using the following relationship:

$$w_{ji}^{l}(k+1) = w_{ji}^{l}(k) - \eta \frac{\partial E(k)}{\partial w_{ji}(k)} \ldots\ldots\ldots\ldots(5)$$

where η is a constant that determines the rate of learning of the back-propagation algorithm.

3. FERTILIZER APPLICATION EQUIPMENTS

In Brazil, the fluid fertilizer applicator equipments used in sugar cane controls the flow by branching (Figure 4). The flow of the centrifugal pump is split into one stream, which is redirected into the tank, and another stream, which is fed into the spreading nozzles (Miagle, 1996). The recirculation flow is vary important because it sustains the stability of the agricultural suspensions avoiding sedimentation and syneresis (Palgrave, 1991).

In this case, an average application rate is used to apply the fertilizer across the field, and the tractor speed and engine speed should be fixed. Since the tractor does not allow controlling these variables and the application rate is fixed, the fertilizer quantity for a certain portions becomes incorrect.

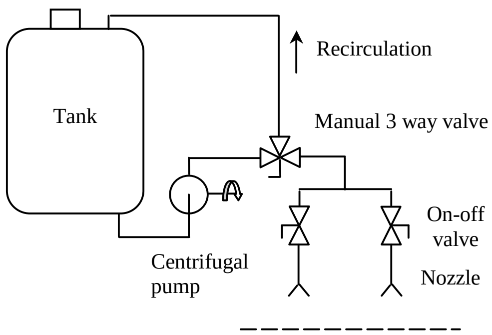

Fig. 4. Fluid fertilizer applicator by branching

On other hand, the application process through variable rates can be made through control systems implemented by conventional techniques with feedback as illustrated in Figure 5. In other words, the measurements from a fertilizer flow meter is used to maintain a pre-set application rate come from a fertility map. All these systems are based on maps, so a GPS (Geographic Positioning System) or DGPS (Differential Geographic Positioning System) becomes necessary. Normally, a magnetic inductive flow meter is used since the fertilizer formulations are suspensions. However, it represents up to 36% of the total cost of a fluid fertilizer applicator. Besides, this device presents dynamics responses very slow or instable for several control propose. Munack, *et al.* (1999) has showed a typical response for a magnetic inductive device. For typical devices, the time delay is 0,5 to 1,2 seconds followed by a lag time of 0.25 to more 1 second.

The flow control may be controlled by control valve or variable speed pump. The control valve may be activated by electric actuator or hydraulic cylinder. For sphere valves with electric motor the time needed for a full opening (10º to 90º) was measured as 5.0 ... 12 s and 0.4 … 1 s for hydraulic cylinder.

Consequently, the control process with feedback can become very slow when used electric actuator or marginally unstable when used hydraulic cylinder due to delays of response provided by magnetic inductive device. Besides, the electric conductivity of fertilisers varies depending on temperature and concentration. So, control systems with electromagnetic flow meter need frequents calibrations.

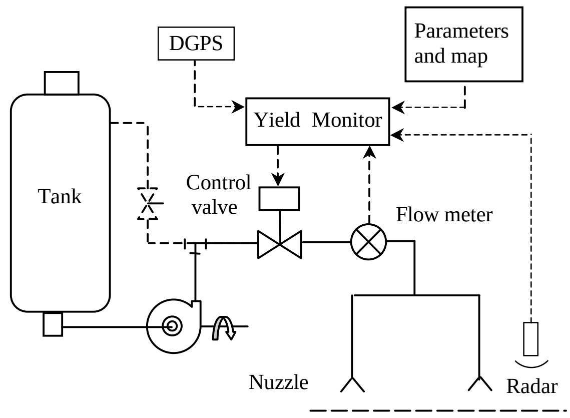

Fig. 5. Fluid fertilizer variable rate applicator system with conventional feedback control.

4. INFERENTIAL CONTROL STRATEGY

In order to achieve a cheap, fast, robust and stable control system, an approach based on Artificial Neural Networks was designed and implemented, as illustrated in Figure 6. The control system uses secondary measurements to identify and control the fertilizer application rate. There is no flow meter devices in the system, indicating an inferential control strategy. Its schematic diagram is shown in Figure 7.

In this system there are two ANN. The output of ANN 1 produces the application rate in function of the GPS or DGPS coordinates (Ulson, *et al.* 2000). The last one (ANN 2) estimates the fluid fertilizer flow rate (q_e). The fertilizer flow rate $q(x,t)$ is controlled through a sphere valve with electric actuator. The flow rate $q(x,t)$ is a nonlinear function of the valve position (α), hydraulic suction head (Z_S), speed pump (ω), nozzle diameter (DB), number of nozzles in operation (NB), fertilizer temperature (Tp) fertilizer specific mass, fertilizer apparent viscosity, particles size in suspension (undissolved nutrients and clay added), etc. This factors affect all loss load in the hydraulic system. Therefore, there are no precise mathematics models that describe the hydraulic process.

So an Artificial Neural Network (ANN 2) of the type multilayer perceptrons is used for the identification and control of the fluid fertilizer application rate.

The net training is made off-line by the algorithm of Levenberg-Marquardt (Hagan and Menhaj, 1994) with training data obtained from workbench measurements.

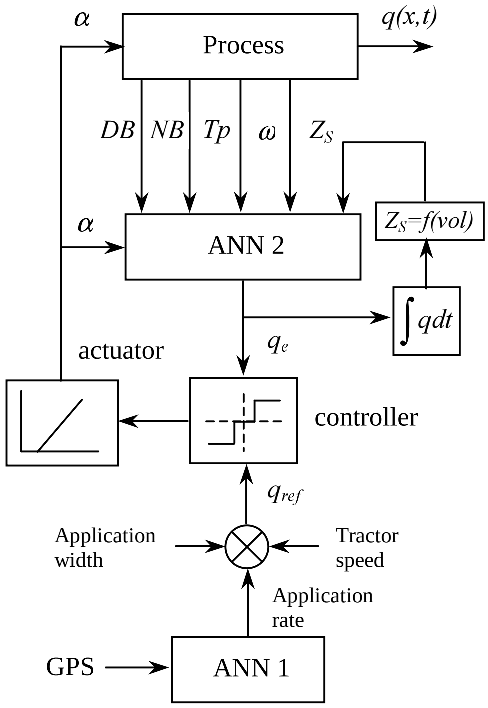

Fig. 6. Block diagram of the inferential control system based on ANN for fluid fertilizer application.

5. DISCUSSION AND RESULTS

For evaluation of the inferential control system, some preliminary tests were accomplished with two NPK fertilizer as following:

i) Fluid fertilizer: NPK 32-0-0 (uan)

This test was realized under the following conditions:

- ANN 2 topology:
  - Architecture: multilayer perceptron (MLP)
  - Number of hidden layers: 1
  - Number of neurons of the hidden layer: 25
- Data set training: 871 vectors
- Data test pattern: 200 vectors
- Cultivation: sugar cane
- Fertilizer temperature: 26.5 °C
- Application width: 3.6 meters
- Number/diameter of nuzzles: 4/∅5 mm
- Tractor speed: 5 … 12 km/h
- Valve angle position: 5 … 90°

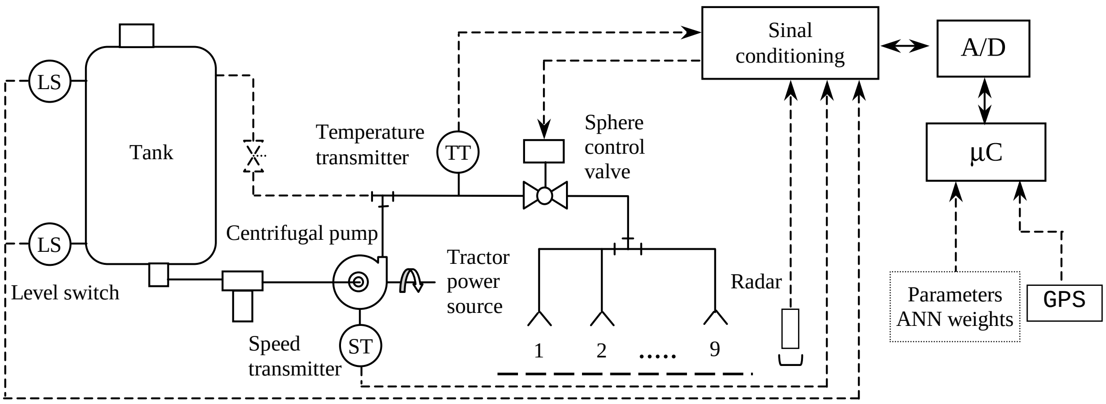

Fig. 7. Basic schematic diagram of the system control bases on ANN for application of fluid fertilizer

It is observed in Figure 8 that the proposed neural approach provides flow rates near to real values. The correlation coefficient (R-value) between measured flow rates and those provide by the ANN 2 is close to 1, which indicates a good ANN generalization. The mean relative error obtained was 2,91% and its standard deviation was 3,56%. Some relative errors are appreciable, but during the application operation their life time is very low, so their effect is not significant.

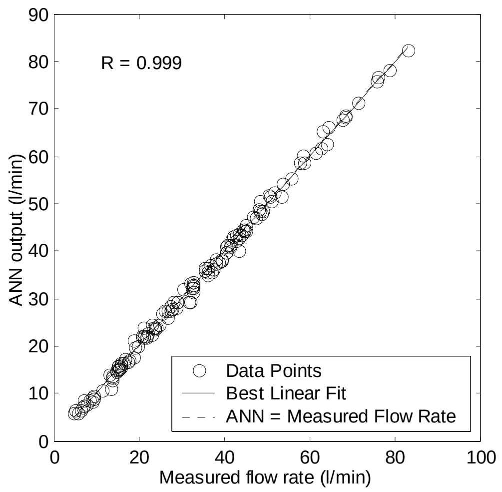

Fig. 8. Correlation between measured flow rate and provided by the ANN 2.

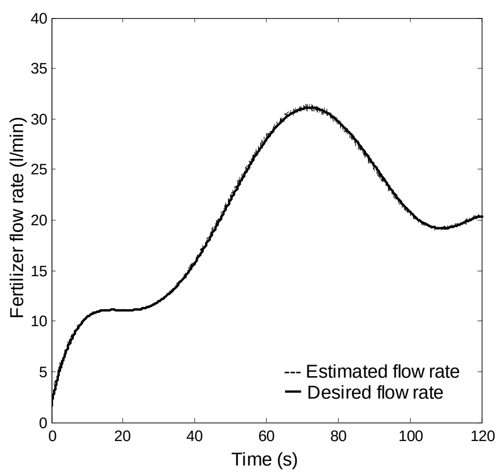

Fig. 9. Behaviour of the intelligent system control.

The Figure 9 shows the system behaviour under agricultural field operation. The desired flow rate is close to the flow rate estimated by the ANN. The fertilizer volume required in the area was 41,0 l and the measured volume was 39,60 l. So, the volume error was 3,53%. This value indicates a good precision for maps-based variable rate fertilizer applicator proposed in this paper.

ii) Fluid fertilizer: NPK 15-0-15 (suspension)

This test was realized under the following conditions:

- ANN 2 topology:
  - Architecture: multilayer perceptron (MLP)
  - Number of hidden layers: 1
  - Number of neurons of the hidden layer: 25
- Data set training: 675 vectors
- Data test pattern: 150 vectors
- Cultivation: sugar cane
- Fertilizer temperature: 26.5 °C
- Application width: 3.6 meters
- Number/diameter of nuzzles: 4/∅5.5 mm
- Material of the nuzzles: inox 316
- Tractor speed: 5 … 15 km/h
- Valve angle position: 10 … 90°
- Flow rate range: 5…50 l/min

The test result for suspensions indicates a precision close to the uran. The mean relative error obtained was 2,76% and its standard deviation was 3,75%. However, for agricultural suspensions, the nuzzles should be made of porcelain to minimize the erosion due to abrasion. To avoid clogging in the control valve, the operational angle (α) must be greater than 10°.

An important aspect in this approach is the transient response of the system when a step excitation is applied. The settling time observed in Figure 10 decreases the precision of the applicator in the field boundary. This problem can be minimized whether the system always to keep its operation close to desired flow rate value. So, it is necessary electric on-off valves near the nuzzles to start the application in the field boundary.

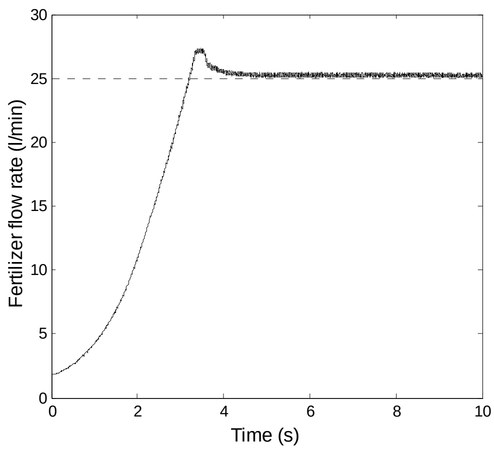

Fig. 10. Step response of the intelligent control system using a control valve with 12 s for full opening.

6. CONCLUSIONS

The proposed method provides a systematic approach to control the application of fluid fertilizer across the field and others agricultural products such as: solid fertilizers, pesticides and seeds. The test results demonstrate that the proposed approach is an efficient alternative to the conventional models that are usually used in these processes. The main advantages in using the proposed approach are: i) the flow meter can be removed, allowing a reduction up to 36% in the equipment cost ii) simplicity of implementation, iii) very good precision for precision farming, iv) economy of agricultural inputs, v) reduction of environmental impacts and vi) effective obtainment of economical and operational gains.

In sake of a better understanding, the system has still been developed. Several fluid fertilizer formulation will be considered to validate the proposed approach.

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