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Full Length Research Paper

Utilizing an Adaptive Neuro-Fuzzy Inference System for the Optimal Distribution of Liquid Pesticides

Khalid A. Al-Gaadi[1]*, Abdulwahed M. Aboukarima[2] and Ahmed A. Sayedahmed[3]

[1]Department of Agricultural Engineering, Precision Agriculture Research Chair, College of Food and Agricultural Sciences, P. O. Box 2460, King Saud University, Riyadh 11451, Saudi Arabia. [2]Huraimla Community College, P. O. Box 300, Shaqra University, Huraimla 11962, Saudi Arabia. [3]Department of Agricultural Engineering, College of Food and Agricultural Sciences, P .O. Box 2460, King Saud University, Riyadh 11451, Saudi Arabia.

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An adaptive neuro-fuzzy inference system (ANFIS) was implemented to evaluate different combinations of nozzle flow rates and boom heights in terms of liquid pesticide distribution uniformity from a ground field sprayer. In addition, the ANFIS was utilized to determine the optimum combination of the two principal factors (boom height and nozzle flow rate) that would result in the best distribution uniformity. In ANFIS, the two principal factors were selected as inputs, however, the Coefficient of Distribution Uniformity (CDU) was considered as the system output. For the tested set of data, the ANFIS analysis designated a boom height of 60 cm and a nozzle flow rate of 118 L/h as the optimum combination with a CDU value of 65.7%. Results of the study showed that the ANFIS technique was effective in evaluating and classifying the different possible combinations of the involved principal factors for best distribution uniformity. Moreover, results revealed that the utilized ANFIS was accurate in predicting the CDU. The R^2 values for the relationship between calculated CDU and ANFIS predicted CDU were 0.992 and 0.988 for the training and testing stages, respectively.

Key words: Pesticides, nozzle flow rate, boom height, ground field sprayer, adaptive neuro-fuzzy inference system, coefficient of distribution uniformity.

INTRODUCTION

The concerns of public and environmentalist about the bad effects that agricultural chemicals, such as pesticides, can cause to the environment are rapidly increasing. These concerns have led to an urgent need for judicious use of these pesticides in agriculture and more accurate pesticide field applications. It has been shown by a number of studies that the accuracy of liquid pesticide applications has mainly been affected by two factors; the flow rate out of the spray nozzles and the vertical distance between the spray boom and the treated surface (boom height). Therefore, researchers have, in many studies, investigated these two factors and revealed their effects on the accuracy of the spraying operations, which has to be maintained at a level that is satisfactory to farmers and environmentalists. Peterson et al. (1993) observed that the performance of a utilized spraying system was found to be greatly affected by the characteristics of the nozzle tip used, including droplet size, flow rate, spray angle and spray distribution pattern. On the other hand, boom height was reported to be the most significant variable in the prediction equation for the spray drift (Bode et al., 1976). They reported that even a small increase in the boom height (from 43 to 58 cm) could cause a major difference in the drift equation outcome, making it a very critical factor in predicting total drift and system accuracy. Drocas et al. (2009) reported that, for a ground field sprayer, the two most important factors affecting the liquid pesticide distribution uniformity were the boom height from the treated surface and the used nozzle type. For a specific pressure value, Faqiri

*Corresponding author. E-mail: kidaag@gmail.com /kgaadi@ksu.edu.sa. Tel: 0096614678396/00966555151614. Fax: 0096614678502.

Abbreviations: ANFIS, Adaptive neuro-fuzzy inference system; **CV,** coefficient of variation; **CDU,** coefficient of distribution uniformity; **RMSE,** root mean square error; **VAF,** variance account for.

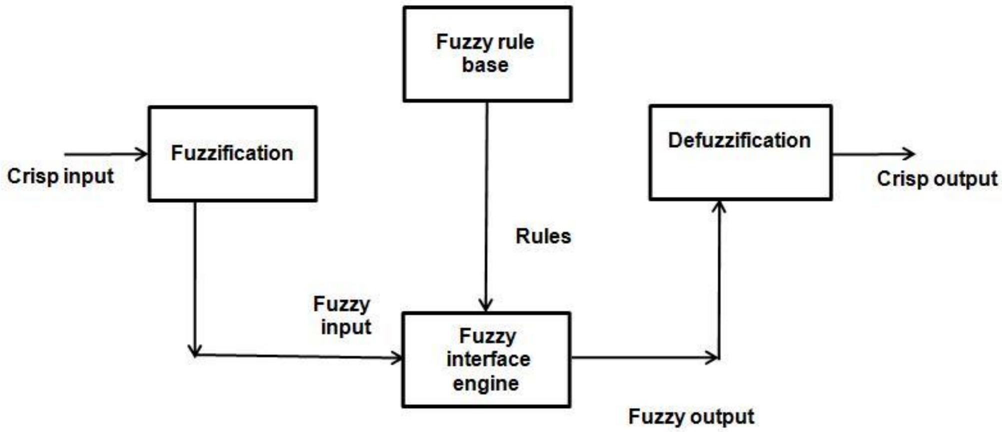

Figure 1. General structure of a fuzzy logic system (Zhang, 2009).

and Krishnan (2005) found, in a laboratory test, that different nozzle types produced different coefficient of variations (CV) in the spray deposit, hence, different distribution uniformities. The CV was not affected by the pressure in the pressure range of 138 to 345 kPa incorporated in the study, however, it was found to decrease with increasing boom height at all test pressure values. Womac et al. (2001) utilized a pattern table to study the CV in a spray deposit for seven different nozzle types and four different boom heights (ranging from 41 to 112 cm) at three pressure values (ranging from 276 to 552 kPa). The CV was found to range, depending on nozzle type, from 6.8 to 13.6% at a pressure of 552 kPa and a boom height of 41 cm. At a specific pressure value and nozzle type, different boom heights produced different CV values. However, each nozzle type exhibited an optimum boom height at a specific pressure value, where the CV was at its minimum value, indicating optimum uniformity. Wang et al. (1995) tested the distribution uniformity at three boom heights, and suggested that there was an optimum boom height at which the degree of non-uniformity could be minimized.

Techniques, such as fuzzy logic (inference) system, have been widely used as efficient tools for modeling and forecasting of complex systems (Yan and Wang, 2010). This rule-based system is mainly composed of three conceptual components (Zhang, 2009). The first component is a fuzzy rule base containing a selection of fuzzy IF-THEN rules. The second component, however, is a database defining the membership functions used in the fuzzy rules. The third component consists of an inference system to perform the inference procedure upon the rules to derive an output. The fuzzification is a procedure to convert the crisp inputs into fuzzy inputs. The fuzzy inference engine utilizes fuzzy logic principles, fuzzy IF-THEN rules and fuzzy input to provide a fuzzy output for defuzzification, where a crisp output is extracted from a fuzzy set (Figure 1).

Fuzzy logic system is mostly used by researchers to reach a definite conclusion from imprecise data, where uncertain, vague, or missing input information exists (Selvi, 2009). The use of imprecise information through fuzzy logic for quantitative evaluation of the available data was initially proposed by Zadeh (1965). This approach was reported to be based on logical relationship between input and output factors connected by IF-THEN statements, and not on mathematical equations or assumptions (Ozger and Yildinm, 2009). Ozger and Yildinm (2009) provided a description of the structure of the fuzzy rules and stated that the number of rules was dependent on the nature of the problem concerned. For fuzzy inference systems, there are mainly two approaches; the Mamdani approach (Mamdani and Assilian, 1975) and the Sugeno approach (Takagi and Sugeno, 1985). The difference between the two approaches lies in the consequent part, where fuzzy membership functions are used in Mamdani and linear or constant functions are used in Sugeno. In addition, availability of data is a required to apply the Sugeno approach; however, this is not a requirement in Mamdani approach (Ozger and Yildinm, 2009).

In biological and agricultural applications, the fuzzy logic system was reported by Center and Verma (1998) to be a powerful concept for handling non-linear, time-varying and adaptive systems. Distribution uniformity of liquid pesticides applied by ground sprayers is a determining factor that greatly influences the effect of the treatment on the pest controlled and on the surrounding environment. For a ground field sprayer, the liquid pesticide distribution uniformity is mostly affected by boom height and nozzle type (Drocas et al., 2009). Therefore, statistical measures have been widely used to report the effect of these two factors on the distribution uniformity of agrochemicals from ground field sprayers. Fuzzy inference methods have recently been proposed as a means to understand and assess the complex relationships among indicators in agricultural systems (Center and Verma, 1998). However, a lack of knowledge

Table 1. Specifications of nozzle types used in the experiments (Al-Gaadi, 2010).

Nozzle type	Nozzle code	Nozzle flow rate (L/h)
Flat fan – low drift	ADI 04	148.0
Flat fan – low drift	ADI 03	100.8
Flat fan – low drift	ADI 02	77.6
Flat fan	AXI 02	75.8
Hollow cone	JA-4	107.5
Hollow cone	JA-2	51.7

exists in the field of applying fuzzy inference methods in evaluating the distribution uniformity of agrochemicals. Therefore, the overall goal of this study was to investigate the performance of an adaptive neuro-fuzzy inferences system (ANFIS) in evaluating different combinations of nozzle flow rates and boom heights in terms of resulted distribution uniformity of liquid pesticides.

MATERIALS AND METHODS

Data collection

Data for this study (96 observations) was obtained from a previous field experiment conducted by Al-Gaadi (2010) to investigate the effect of boom height and nozzle type on the performance of a ground field sprayer in terms of liquid spray distribution uniformity. Four different boom heights, namely 15, 30, 45 and 60 cm and six different JACTO^{TM} nozzle types were included in the experiment. Given that a pressure of 600 kPa, a ground speed of 6 km/h and a nozzle spacing of 50 cm along the sprayer boom were known constant test parameters, a static test was conducted to calibrate each nozzle type for flow rate (Table 1), where water was used as the spray liquid. The different coefficients of distribution uniformity were mathematically determined from the different coefficients of variation.

Adaptive neuro-fuzzy inference system (ANFIS)

There are various types of neuro-fuzzy systems; however, the adaptive neuro-fuzzy inference system (ANFIS) is thought to be the most popular. This system employs adaptive neural networks to develop a fuzzy inference system (Jang and Sun, 1993, 1995). The fuzzy inference system proposed by Takagi and Sugeno (1985), known as the TS model, provides a powerful tool for modeling complex nonlinear systems. The TS model is based on the fact that an arbitrary complex system is a combination of mutually inter-linked subsystems. It consists of a set of local input-output relations that describe the overall system. The rules in first-order TS model are in the following structure:

$$R_i : IF\ (x_1 \ is\ A_{i1}\ and\ x_2\ is\ A_{i2}\ and \ldots x_m\ is\ A_{im})\ THEN\ y_i = a_{i1}x_1 + \ldots + a_{im}x_m + a_{i0} \quad (1)$$

Where R_i *(I =1, 2,…, c)* denotes the ith fuzzy rule, x_j (j =1, 2,…, m) are the input (antecedent) variables, y_i are the rule output variables, $A_{i1},\ldots,A_{im}$ are the fuzzy sets defined in the antecedent space, and $a_{i1},\ldots, a_{im}, a_{i0}$ are the model consequent parameters that have to be identified in a given data set. For a given input crisp vector $x = (x_1, \ldots, x_m)^T$, the inferred global output of the Takagi and Sugeno model is computed by taking the weighted average of the individual rules' contributions.

$$\hat{y} = \frac{\sum_{i=1}^{c} \tau_i(x) \cdot y_i}{\sum_{i=1}^{c} \tau_i(x)} \quad (2)$$

Where $\tau_i(x)$ is the degree of fulfillment of the ith fuzzy rule, defined by:

$$\tau_i(x) = Min\left\{\propto_{A_{i1}}(x_1) \ldots \propto_{A_{in}}(x_n)\right\} \quad or$$
$$\tau_i(x) = \propto_{A_{i1}}(x_1) \cdot \propto_{A_{i2}}(x_2) \cdots \propto_{A_{in}}(x_n)\ i = 1, 2, \ldots, c \quad (3)$$

for the minimum and product conjunction operators, respectively. The membership function of the antecedent fuzzy set A_{ij} is:

$$\propto_{A_{ij}} : R \rightarrow [0,1].$$

In order to demonstrate the effectiveness of the fuzzy system, a data set collected during a previous field experiment was used. The fuzzy system (Figure 2) was structured and formulated using Matlab version 6.1 and the fuzzy logic toolbox (Mathworks, 2001), as a Sugeno fuzzy model (TS). The first step in designing the fuzzy logic model was to identify the fuzzy input and output variables. In this study, the two variables of boom height (BH) ranging from 15 to 60 cm and nozzle flow rate (ND) ranging from 51.7 to 148.0 L/h were selected as the fuzzy inputs. However, the coefficient of distribution uniformity (CDU) was considered as the fuzzy output variable. Boom height and nozzle flow rate were partitioned into four domains, low (L), medium (M), high (H) and very high (VH). Because of its simplicity, a triangular membership function was assigned for all fuzzy sets. All of the involved data points (96 observations) were randomized and partitioned into two sets. One set contained 88 pairs and was used for training process, while the other set of 8 pairs was utilized for testing process. The number and the type of the membership functions assigned to the input variables were chosen adopting the trial and error approach. After a 100 epochs, the model adapted the parameters of the membership functions by hybrid learning using the ANFIS function of the Matlab fuzzy logic toolbox (Mathworks, 2001), with a training error of 1.09. Five network layers are used by the developed ANFIS to perform the following fuzzy inference steps:

1) Input fuzzification.
2) Fuzzy set database construction.
3) Fuzzy rule base construction.
4) Decision making.
5) Output defuzzification.

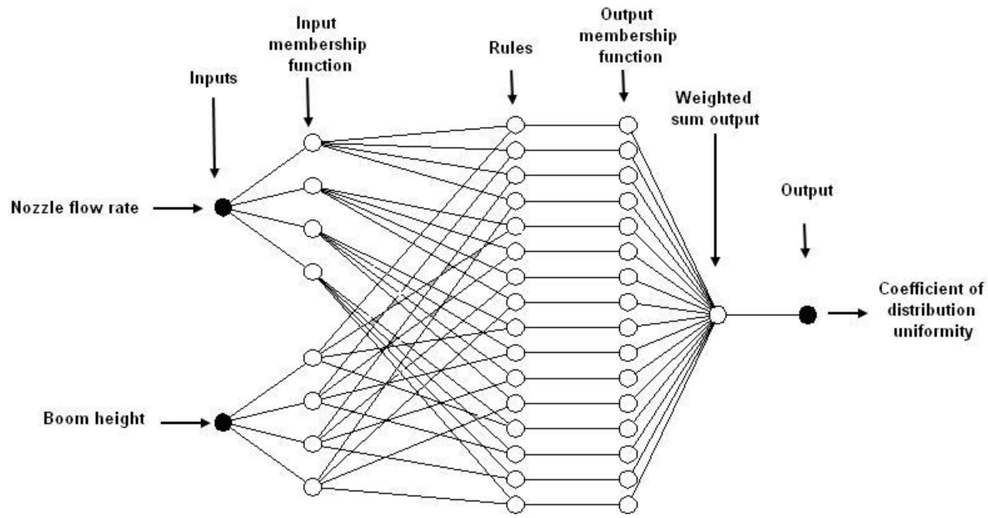

Figure 2. ANFIS structure for determining CDU with two input variables and 16 rules.

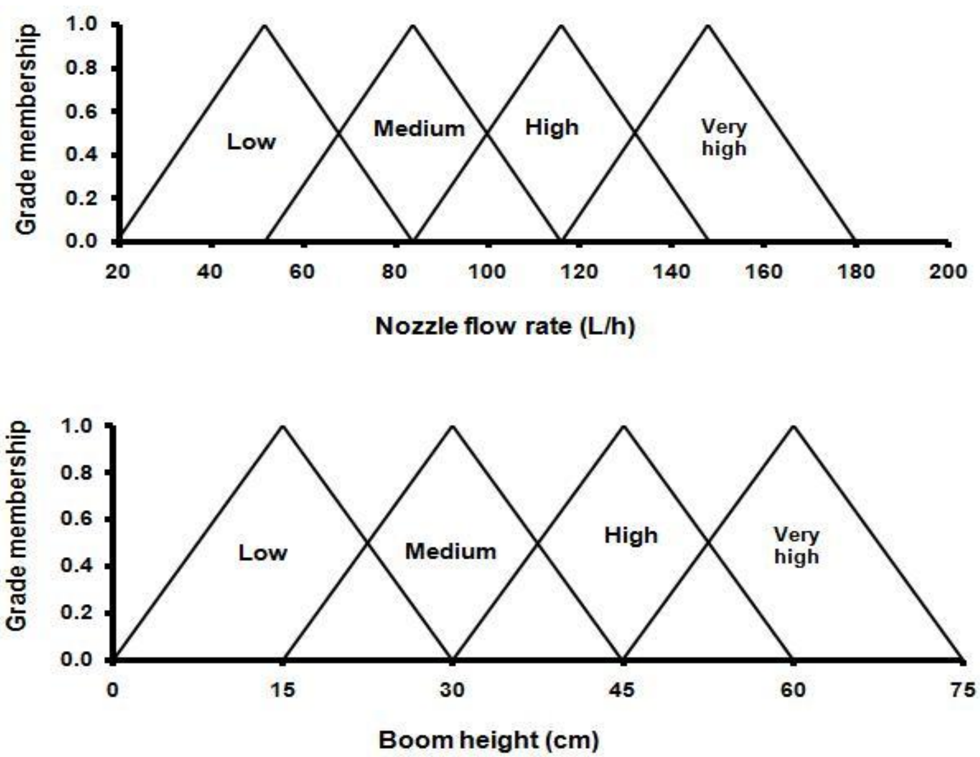

Figure 3. The fuzzy membership functions for the inputs of nozzle flow rate and boom height.

This is a multi-layered neural network architecture, where the first layer represents the antecedent fuzzy sets, the middle layers represent the consequent fuzzy sets and the output layer represents the defuzzification strategy (Jang, 1993). Each layer involved several nodes that were described by the node functions. The functions of the various layers are explained by Jang and Sun (1997). The form of the membership functions after the training process is shown in Figure 3. The number of rules defined in the TS model is a product of the number of membership functions in each input. Therefore, the developed model contained 16 (4 × 4) rules and the description of each rule after training process was explicitly presented in Table 2.

Model performance

The performance of the developed model was assessed using various standard statistical performance evaluation criteria. The root

Table 2. Fuzzy scaling rules of the developed model.

Rules	Nozzle flow rate (X1, L/h)	Boom height (X2, cm)	Empirical constants of the coefficient of distribution uniformity without overlap
Rule 1	Low	Low	Y1 = 10.84 × X1-34.98 × X2 - 2.332
Rule 2	Low	Medium	Y2 = 3.119 × X1 - 4.206 × X2 - 0.1402
Rule 3	Low	High	Y3 = 0.07364 × X1 + 1.126 × X2 + 0.02502
Rule 4	Low	Very high	Y4 = 0.4837 × X1 + 0.6017 × X2 + 0.01003
Rule 5	Medium	Low	Y5 = 3.525 × X1 - 21.48 × X2 - 1.432
Rule 6	Medium	Medium	Y6 = 1.656 × X1 - 3.626 × X2 0.1209
Rule 7	Medium	High	Y7 = 0.7326 × X1 - 0.06535 × X2 - 0.001452
Rule 8	Medium	Very high	Y8 = 0.1039 × X1 + 0.7726 × X2 + 0.01288
Rule 9	High	Low	Y9 = -4.497 × X1 + 32.41 × X2 + 2.161
Rule 10	High	Medium	Y10 = -1.32 × X1 + 5.392 × X2 + 0.179
Rule 11	High	High	Y11 = 0.3473 × X1 - 0.007193 × X2 - 0.000159
Rule 12	High	Very high	Y12 = 0.6619 × X1 - 0.1801 × X2 - 0.003002
Rule 13	Very high	Low	Y13 = 0.1586 × X1 + 0.01607 × X2 + 0.00107
Rule 14	Very high	Medium	Y14 = 0.2342 × X1 + 0.04747 × X2 + 0.00158
Rule 15	Very high	High	Y15 = 0.3027 × X1 + 0.09204 × X2 + 0.00205
Rule 16	Very high	Very high	Y16 = 0.2949 × X1 + 0.1195 × X2 + 0.00199

mean square error (RMSE) was selected as the common performance measure that could efficiently reveal the general quality of the fit. For a perfect fit, the RMSE should, mathematically, be equal to zero. The RMSE was determined using the following formula (Makridakis et al., 1998):

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(Y_{ai} - Y_{pi}\right)^2}{n}} \quad (4)$$

To explore the degree at which the developed models can explain the variance in the data, the variance account for (VAF) parameter was used as a performance index as follows (Aqil et al., 2006):

$$VAF = \left[1 - \frac{var\left(Y_{ai} - Y_{pi}\right)}{\mathrm{VAR}\left(Y_{ai}\right)}\right] \cdot 100 \quad (5)$$

Where RMSE is the root mean square error, Y_{ai} and Y_{pi} are the CDU from experimental calculation and CDU from ANFIS, respectively, *i* is an integer which denotes the number of testing or training data points starting from 1 to n, and var denotes the variance. In general, the closer the VAF to 100%, the better the model performs. The coefficient of determination (R^2) was selected to measure the linear correlation between the CDU from experimental calculation and CDU from ANFIS. The optimal correlation coefficient value is unity.

RESULTS AND DISCUSSION

A graphical depiction of the sixteen rules generated to map the input data (antecedent) with the output (consequent) for the coefficient of distribution uniformity in the ANFIS is shown in Figure 4. Each rule, as shown in the Figure, is represented by an individual row, while variables are represented by individual columns. The first two columns depict the membership functions for the two input variables of nozzle flow rate (ND) and boom height (BH), referenced by the antecedent or the "if-part" of each rule. The third column, however, which consists of sixteen plots, shows the membership functions used by the consequent or the "then-part" of each rule. The vertical lines in the first two columns indicate the current data inputs for ND and BH to be 118 L/h and 60 cm, respectively. The bottom plot in the right column represents the aggregate of each consequent, whereas, the defuzzified output value is represented by a thick line passing through the aggregate fuzzy set. For the current data inputs (ND of 118 L/h and BH of 60 cm), the defuzzified output is shown to be 65.7% (Figure 4). For the ground speed and the range of nozzle pressure values used in the field experiment, the values of the current data points were found to produce the best CDU considering all treatments included in the experiment.

As the training process of the developed model was completed, the model evaluation and testing stage took place. The output of the model, the predicted coefficient of distribution uniformity (predicted CDU), was compared with the coefficient of distribution uniformity calculated from actual field data collected during field experiments (calculated CDU). A graphical representation of the predicted CDU versus calculated CDU is depicted in Figure 5. The data points in Figure 5 seemed to form a straight line, which was an indication that the tested model was fairly accurate in predicting the CDU. In addition, the values of the performance indices of the ANFIS model during training and testing stages (Table 3) confirmed the high accuracy of the employed model. As

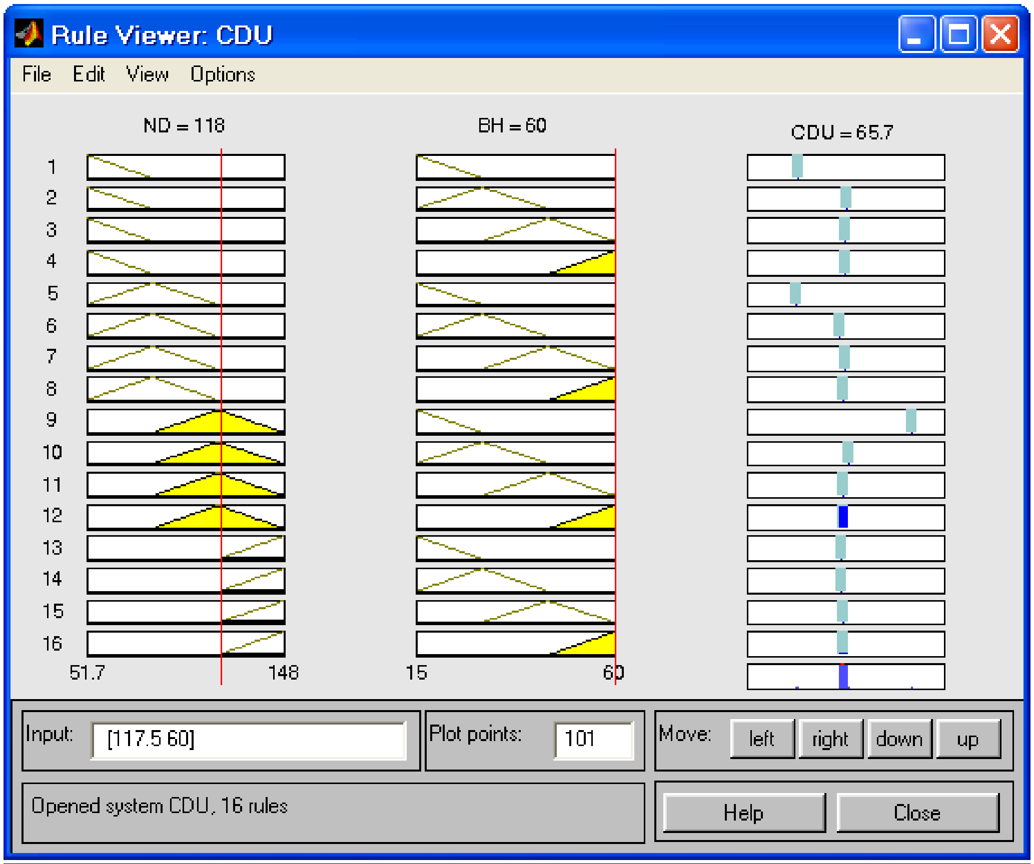

Figure 4. Graphical representation of the rules.

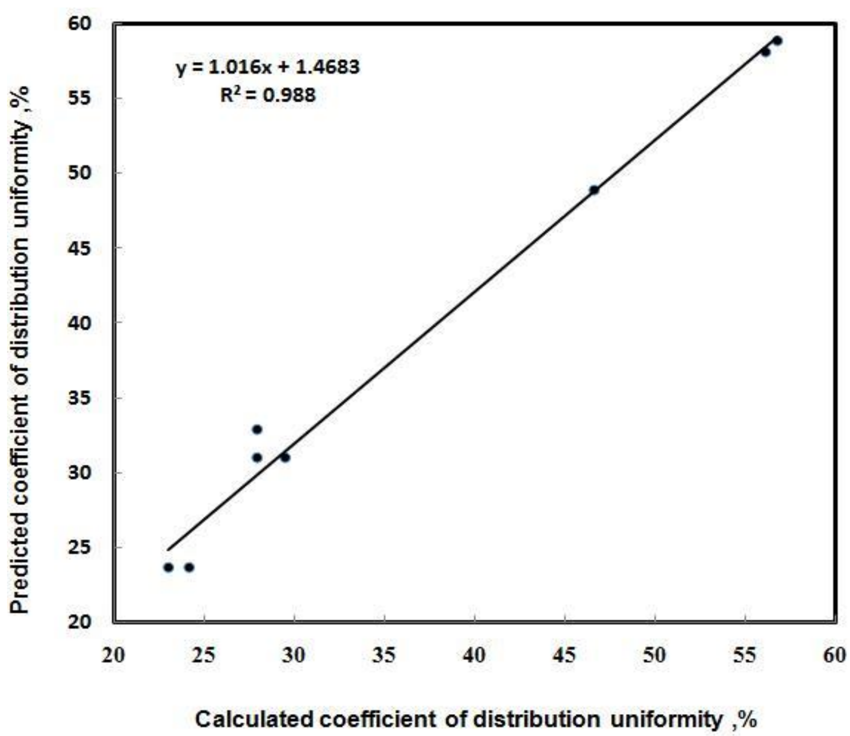

Figure 5. Predicted versus calculated CDU during testing stage.

Table 3. Indicators of the ANFIS model accuracy in predicting CDU during training and testing stages.

Criteria of accuracy	Units	Value	
		Training stage	Testing stage
Root mean square error (RMSE)	(%)	1.10	2.54
The "variance account for'' (VAF)	(%)	99.24	98.75
Coefficient of determination (R^2)	(----)	0.992	0.988

evidenced by Figure 5 and Table 3, the developed model provided the best fit to the observed results and produced an accurate prediction of the coefficient of distribution uniformity. The RMSE, which evaluates the residual between calculated and predicted CDU, VAF and R^2 values all suggested that the developed model exhibited a performance that promoted it to predict the CDU with a high degree of accuracy. Therefore, the model was thought to be accurate enough to be used as an integral part of a decision support system that could help in determining the optimum combination of nozzle flow rate and boom, height that would produce the best chemical distribution. As a result, more accurate applications could be achieved for the benefit of farmers and agricultural environment. In addition, the ANFIS offers a simple, but rather effective, method to study the effect of different input variables on spray distribution uniformity. Therefore, it provides a promising prospective tool that can be efficiently utilized to evaluate and assess the performance of the widely used field ground sprayers.

Conclusions

An Adaptive Neuro-Fuzzy Inference System (ANFIS) was developed and tested for its accuracy in evaluating the performance, in terms of spray distribution uniformity, of different combinations of nozzle flow rates and boom heights. Specific conclusions can be outlined as follows:

1. The developed ANFIS was capable of classifying the different combinations of sprayer boom height and nozzle flow rate and outputting the optimum combination that would deliver the best spray distribution uniformity. For the data tested, the ANFIS output indicated that the boom height of 60 cm and the nozzle flow rate of 118 L/h was the optimum combination with a CDU value of 65.7%.
2. Comparison of the ANFIS-predicted CDU values with those calculated from field-collected data showed that the ANFIS was accurate in its prediction. In the training stage, the RMSE and VAF values were 1.10 and 99.24%, respectively, where these values were 2.54 and 98.75%, respectively during the testing stage. On the other hand, the relationship between ANFIS-predicted and calculated CDU was found to be linear with R^2 values of 0.992 and 0.988 during the training and the testing stage, respectively.
3. The ANFIS technique can be efficiently utilized to evaluate the performance of ground sprayers at different operating conditions, such as nozzle flow rate and boom height. Moreover, the technique can be employed as an important component of a decision support system. This system can be designed to be interrogated by ground sprayer operators for the combinations of operating conditions that would deliver the optimum distribution uniformity of liquid pesticides. Hence, the technique is thought to have a great impact on the agro economics and the environment.

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