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Neural modeling and optimization of the coverage of the sprayed surface

B. CIENIAWSKA*, K. PENTOŚ, and D. ŁUCZYCKA

Wrocław University of Environmental and Life Sciences, ul. C.K. Norwida 25, 50-375 Wrocław, Poland

Abstract. Improving application efficiency is crucial for both the economic and environmental aspects of plant protection. Mathematical models can help in understanding the relationships between spray application parameters and efficiency, and reducing the negative impact on the environment. The effect of nozzle type, spray pressure, driving speed and spray angle on spray coverage on an artificial plant was studied. Artificial intelligence techniques were used for modeling and the optimization of application process efficiency. The experiments showed a significant effect of droplet size on the percent area coverage of the sprayed surfaces. A high value of the vertical transverse approach surface coverage results from coarse droplets, high driving speed, and nozzles angled forward. Increasing the vertical transverse leaving surface coverage, as well as the coverage of the sum of all sprayed surfaces, requires fine droplets, low driving speed, and nozzles angled backwards. The maximum coverage of the upper level surface is obtained with coarse droplets, low driving speed, and a spray angle perpendicular to the direction of movement. The choice of appropriate nozzle type and spray pressure is an important aspect of chemical crop protection. Higher upper level surface coverage is obtained when single flat fan nozzles are used, while twin nozzles produce better coverage of vertical surfaces. Adequate neural models and evolutionary algorithms can be used for pesticide application process efficiency optimization.

Key words: spray nozzle, spraying efficiency, spray coverage, artificial neural network, genetic algorithm.

1. Introduction

The constantly growing demand for food is a critical factor in modern agricultural engineering. Therefore, chemical plant protection is important, since it is linked to increases in crop yield and labor productivity. However, it can also have a serious, negative impact on the environment. Therefore, improving application efficiency is among the most important current issues with regard to plant protection. It is also one of the goals of the 128/2009/EC European Directive for a Sustainable Use of Pesticides [1]. Pesticide-related pollution is a serious environmental problem caused by over-application, drift to unintended targets, and the contamination of surface and ground water [2]. The potential risks of pesticide use to the environment, as well as to animal and human health, have been emphasized by many researchers [3, 4]. In many countries, governments have made efforts to reduce the negative effects of pesticide application, e.g. by incorporating drift-reducing spray nozzles [5] or spray buffers and breaks [6].

Examining the literature in the spray application techniques field showed that several studies have been conducted in the last few years to evaluate the effect of various factors on the parameters that describe application process efficiency, such as spray drift, spray deposition, or coverage. The spray characteristics of agricultural spray nozzles have been reported to affect the efficiency of the application process [7, 8]. Also, parameters such as droplet size distribution (which depends on the nozzle type and working pressure) [9–11] as well as the driving speed [12], boom height [13], spray angle [14], spray solution characteristics (additives, density, surface tension, and viscosity) [5, 15], weather conditions [16], and target canopy characteristics [17, 18] have been noted as significant influences on spray application efficiency.

Spray application efficiency assessment can be performed based on percent area coverage (PAC) of the sprayed surfaces. The results are obtained from image software analysis of collectors, often made from water-sensitive paper [19–21]. The measurements are performed in the laboratory or under field conditions, and collectors are placed on artificial or natural plants [12, 22, 23].

Mathematical models can be used to understand the relationships between environmental and technical parameters and spray application efficiency, as well as to reduce the negative effects of pesticide application. Both analytical predictive models and numerical models have been developed by researchers. The analytical models, with no physical basis, cannot cover a wide range of environmental and operating parameters, but are not computationally demanding. On the other hand, numerical models with a strong physical basis are accurate for a wide range of conditions, but require higher computing power. Much of the existing literature has focused on spray drift prediction, and several mechanistic models have been proposed: the OML-SprayDrift model [24], a 3D fully mechanistic model [25], a 2-D diffusion–advection model [26], a Gaussian plume model [27], and BREAM (Bystander and Resident Exposure Assessment Model) [28]. When the investigated relationships are multi-dimensional and highly nonlinear, the use of artificial intelligence methods, such as artificial neural networks (ANNs), can produce sufficiently accurate models. It has been

*e-mail: beata.cieniawska@upwr.edu.pl

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well documented that ANNs have several applications in many scientific fields for solving regression and classification problems. Furthermore, an ANN model can be used as an objective function in the optimization process [29].

According to many growers, the present-day spray application techniques are insufficient and need to be improved. According to [30, 31] there is still need for the improvement of spray application techniques, and for the development of methods for the determination of the optimal settings and nozzle choice for spray boom equipment. A great deal of research has already been carried out to investigate the effect of droplet size on spray coverage and application process efficiency, but relatively few studies have explored the effect of spray angle and driving speed.

The objectives of the present study are:

(i) The development of ANN models of the relationships between percent area coverage of sprayed surfaces and nozzle type, spray pressure, driving speed, as well as spray angle.

(ii) The determination of the input variables' importance in each of the neural models.

(iii) The optimization of application process efficiency by the use of an evolutionary algorithm.

Many researchers emphasize that for a successful spraying process, the choosing of the appropriate nozzle is essential. However, market offers wide range of nozzle types. Therefore, we conducted experiments to increase the scope of information in this research field.

ANNs were used by [32] for yield modeling, by [33] for soil moisture modeling, and by [34] for rotor fault detection.

Finally, ANN techniques give more advantages than just a high precision mathematical model. There are several methods for the determination of the contribution of independent input variables in an ANN model. It gives information about the predictor variables' importance [35–37].

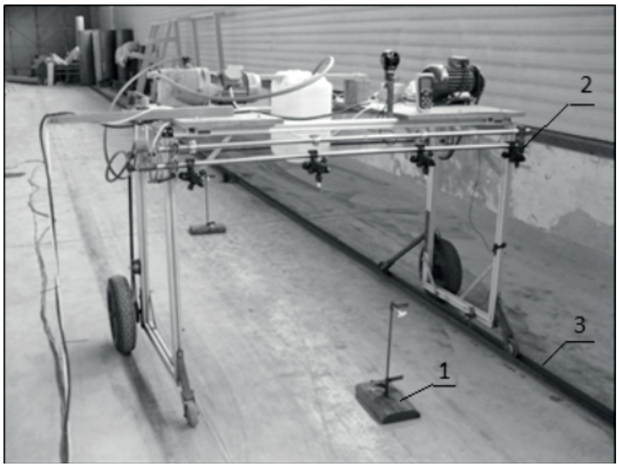

Fig. 1. Experimental set-up: 1 – artificial plant, 2 – spray boom, 3 – metal track guide

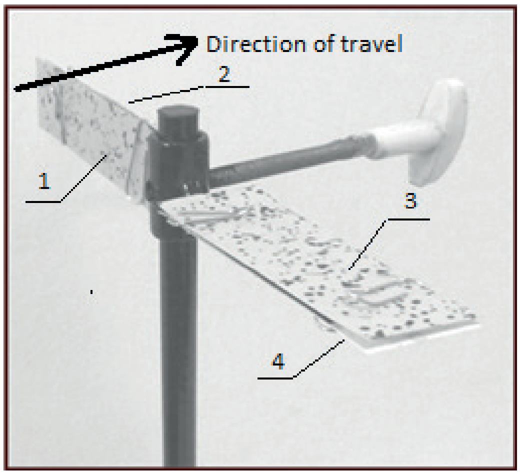

Fig. 2. Artificial plant with collector plant zones: 1 – vertical transverse approach surface, 2 – vertical transverse leaving surface, 3 – upper level surface, 4 – bottom level surface

2. Materials and methods

2.1. Experimental set-up. All spray applications were carried out in controlled laboratory conditions to quantify the effects of nozzle type, spray pressure, driving speed, and spray angle on percent area coverage of four sprayed surfaces. During the research the temperature was 21°C, and the humidity was 55%. A special spray track machine presented in Fig. 1 was designed and constructed to control the boom height, spray angle, driving speed, and working pressure during multiple treatments. A spray boom was moved along a track guide with constant speed. Three artificial plants (=3 replicates) were placed under a spray boom. Newtonian liquid (pure water) was used as the spray liquid.

Water sensitive papers were attached to four collector plant zones: the upper level surface, the vertical transverse leaving surface, the vertical transverse approach surface, and the bottom level surface (Fig. 2).

The coverage of the bottom level surface was not taken into account in further analysis because this surface was not covered by liquid. Samplers as water sensitive papers were used in the research of [38]. Four nozzle types at three different application pressures (200, 300, and 400 kPa) were selected for the test: single standard flat-fan (AXI 11002), single air-induction flat-fan (AVI 11002), twin standard flat-fan (DG TJ60 11002), and twin air-induction flat-fan (AVI TWIN 11002). The boom height was set at 0.5 m, and the nozzles were tested perpendicularly to the direction of movement, angled forward (+20° and +10°), and backward (−20° and −10°), with driving speeds of 1.1, 2.2, 3.3, and 4.4 $m \cdot s^{-1}$.

The spray coverage was assessed with a Nikon MULTIZOOM AZ 100 microscope and NIS Elements Br software for image analysis. Three 10×10 mm squares were randomly selected on water-sensitive paper from each collector.

The color of the area covered by the liquid changed from yellow to blue, and coverage was determined as the percentage of the area colored in blue. Each combination of nozzle and working pressure was classified according to droplet size using

ANSI/ASABE S572.1 reference nozzles [39]. The volumetric droplet size was determined by a laser diffraction instrument (Spraytec, Malvern Instruments). As a result of these experiments, a data set of 720 vectors was obtained. The vector components were as follows: three independent variables – droplet size (affected by nozzle type and spray pressure), driving speed, as well as the spray angle, and three dependent variables – the coverage of the upper level surface (PAC_{ul}), the coverage of the vertical transverse approach surface (PAC_{vta}), and the coverage of the vertical transverse leaving surface (PAC_{vtl}). The statistics of the experimental data are presented in Table 1.

Table 1
The statistics of experimental data

The parameter	Minimum	Maximum	Mean	Standard deviation
Droplet size [μm]	182	553	344	125.2
Driving speed $[m\cdot s^{-1}]$	1.1	4.4	2.8	1.2
Spray angle [°]	–20	20	0	14.1
PAC_{vta} [%]	0	28.5	9.6	5.9
PAC_{vtl} [%]	0	30.9	5.5	4.6
PAC_{ul} [%]	26.1	87.3	54.7	16.4

PAC_{vta} [%] – the coverage of the vertical transverse approach surface;
PAC_{vtl} [%] – the coverage of the vertical transverse leaving surface;
PAC_{ul} [%] – the coverage of the upper level surface.

2.2. Artificial neural network development. ANNs are considered an artificial intelligence technique. They consist of simple processing elements, called artificial neurons, which are arranged in layers. The most popular ANN architecture is Multilayer Perceptron (MLP), also known as a feedforward network, trained using one of the supervised learning algorithms. The theory of ANNs has been described in several papers [40, 41].

An MLP comprises two main layers: an input layer and an output layer, as well as additional (hidden) layers, placed between the input and output layers. The number of nodes in the input and output layers is determined by the number of input and output variables of the model, respectively. The number of neurons in the hidden layers significantly influences the model's quality, and is set by a trial and error approach. The experimental data set containing 720 data vectors was randomly separated into training, test, and validation sets in a 70:15:15 ratio. The data were normalized into a range of 0 to 1. Simulations were performed using Statistica 10 software. An MLP with a single hidden layer was used for the ANN architecture.

The number of neurons in the hidden layer was set to a range of 10 to 30. The transfer functions of the neurons were as follows: sigmoidal, hyperbolic tangent, and exponential. The initial weights and biases of the neurons were chosen randomly.

Three independent ANN models were developed, each with three nodes in the input layer (representing droplet size, driving speed, and spray angle) and with a single neuron in the output layer, producing the predicted value of PAC_{vta}, PAC_{vtl}, or PAC_{ul}. The ANN structure with one neuron in the output layer is presented in Fig. 3.

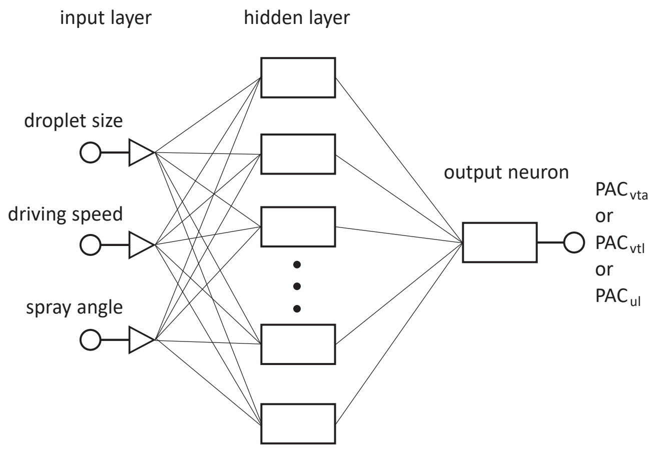

Fig. 3. Structure of the MLP network

For each model, the 300 independent ANNs were trained. Models were generated with the use of Statistica neural network creator which automatically developed neural networks with various number of neurons in hidden layer, initial connection weight vectors, and transfer functions of the neurons. Then the best architecture was chosen for further analysis. Usually in MLP, the transfer function of a neuron in output layer is linear, however, if structure with nonlinear neuron was of better quality, it was considered as the best. Model quality assessment was based on the values of two indicators, the mean square error (MSE) and the coefficient of determination (R^2).

2.3. Methods for quantifying variable importance. In general, when ANNs are used for predictive modeling, they are treated as a "black box." However, ANN models can be used to obtain additional information about investigated relationships, e.g. to determine the contribution of each independent input variable. Two methods to quantify the variables' importance in the ANN model are used in this work: the sensitivity analysis implemented in Statistica 10 and the connection weights method [42]. For various reasons, it is difficult to select the optimal ANN model. Thus, when a single ANN architecture is used for extracting the contribution of variables, the results can be misleading [43]. To avoid this problem, in this work the results of the predictor variables' contributions were calculated for groups of ANN models. From all 300 neural models, the group of forty ANNs with the highest R^2 value and the lowest MSE value was selected. As the final result for each method, the arithmetical mean of the results produced by the forty ANNs was calculated.

2.4. Optimization procedure – evolutionary algorithm. The optimization of spraying conditions was conducted by using a Microsoft Excel 2010 environment.

Since the interaction between spraying conditions and spray quality is nonlinear and complex, the evolutionary algorithm implemented in Excel Solver can be used for the optimization procedure. In previous studies, Excel Solver has been successfully applied to solving optimization problems [44–46].

The evolutionary algorithm implemented in Excel Solver is a hybrid of genetic and evolutionary algorithms and classical optimization methods, such as gradient-free direct search methods and classical gradient-based quasi-Newton methods (Premium Solver Platform, User Guide, 2010). It is a stochastic method, which requires the determination of various algorithm parameters, such as convergence, mutation rate, population size, random seed, and maximum time without improvement. In this research, the algorithm parameters were set as follows: convergence – 0.0001, mutation rate – 0.075, population size – 100, random seed – 0, maximum time without improvement – 30.

3. Results

3.1. Neural models development. Before developing ANN models, the Pearson's correlation coefficients between the explanatory variables should be calculated. The development of an ANN model with linearly dependent predictor variables is a methodological mistake. Furthermore, methods involving an investigation of the relative contribution of an input variable can be ineffective when inputs are interdependent [47, 48]. The values of the Pearson's correlation coefficients are presented in Table 2. The data presented in Table 2 show that the correlation coefficients between the input model parameters are very low, therefore they can be used for neural model development. For each dependent variable, the group of 300 ANN structures was trained with the data set. In each ANN structure the different number of neurons in the hidden layer, the different initial connection weight vectors, and the different transfer functions of the neurons in the hidden and output layers were defined.

Table 2
Correlation coefficients between explanatory variables ($p < 0.05$)

	Droplet size	Driving speed	Spray angle
Droplet size	1.00	0.01	0.01
Driving speed	0.01	1.00	0.01
Spray angle	0.01	0.01	1.00

The parameters of the best ANN architectures are detailed in Table 3. The MSE values were calculated for normalized data.

As shown in Table 3, high values of R^2 and low values of MSE were obtained for the training, test, and validation data sets. The values calculated for the validation data set are crucial in regard to the practical use of the model, and to show its generalization ability. High values, around 0.9, suggest that during the training process no overfitting effects occurred.

Figures 4–6 depict the performance of the predicted values of the PAC of the upper level surface, vertical transverse approach surface, and vertical transverse leaving surface vs. the measured values in the validation set.

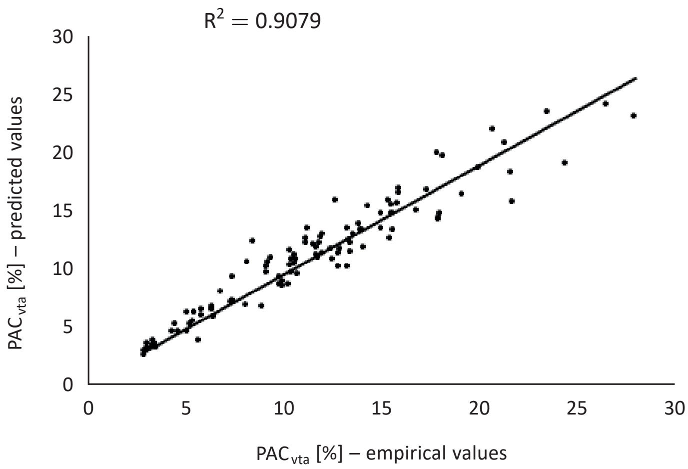

Fig. 4. Predicted values versus measured values of the coverage of the vertical transverse approach surface (validation data set)

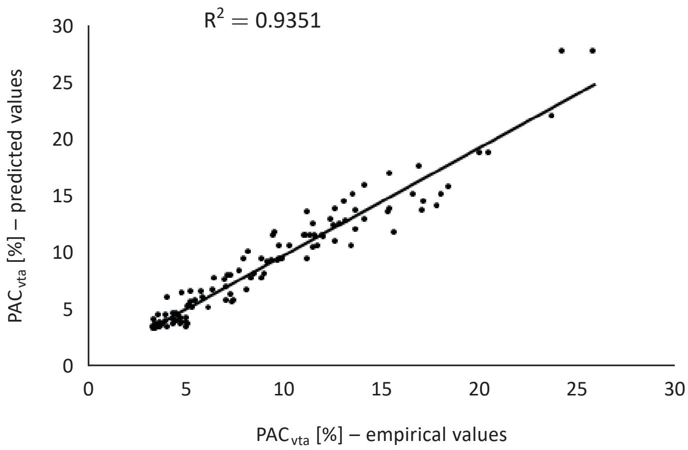

Fig. 5. Predicted values versus measured values of the coverage of the vertical transverse leaving surface (validation data set)

Table 3
The parameters of ANNs used as neural models

Dependent variable	ANN structure	Coefficient of determination R^2			Mean square error (MSE)		
		training data set	test data set	validation data set	training data set	test data set	validation data set
PAC_{vta}	3-14-1	0.88	0.92	0.91	0.002	0.002	0.003
PAC_{vtl}	3-12-1	0.91	0.85	0.94	0.001	0.001	0.001
PAC_{ul}	3-13-1	0.85	0.87	0.92	0.004	0.004	0.004

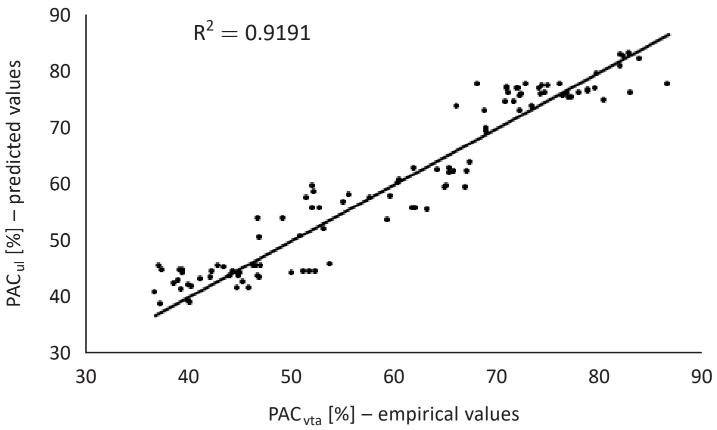

Fig. 6. Predicted values versus measured values of the coverage of the upper level surface (validation data set)

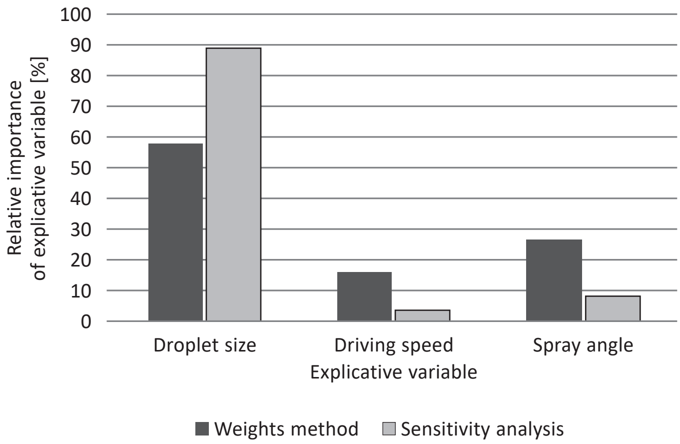

Fig. 7. Comparative of average variable relative importance in the vertical transverse approach surfaces model by methods

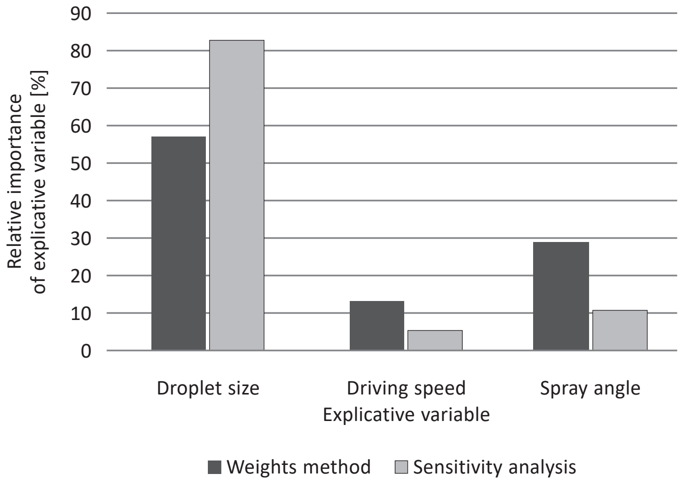

Fig. 8. Comparative of average variable relative importance in the vertical transverse leaving surface model by methods

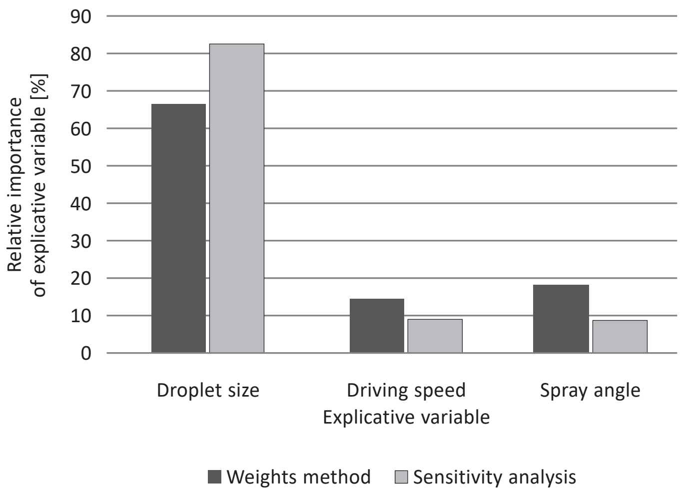

Fig. 9. Comparative of average variable relative importance in the upper level surface model by methods

3.2. Input variables contribution determination. An analysis of the independent input variables' contributions was carried out, based on the group of 40 ANNs chosen from the 300 models that were developed during the training process. The selection criterion was an R^2 value calculated for the validation data set. The number of neurons in the hidden layer was set in the range of 10 to 22; the coefficient of determination values were between 0.89 and 0.91 in the case of the PAC_{vta} regression model, between 0.93 and 0.94 in the case of the PAC_{vtl} regression model, and between 0.91 and 0.92 in the case of the PAC_{ul} regression model. The results of the relative importance of the input parameters for each model are presented in Figs. 7–9.

As illustrated in Figs. 7–9, the results calculated by both methods were comparable. The droplet size, which was affected by the type and pressure of nozzles, had the highest influence on all output parameters (the coverage of the upper level surface, the coverage of the vertical transverse approach surface, and the coverage of the vertical transverse leaving surface). Significantly lower impacts were observed in the case of driving speed and spray angle.

3.3. Optimization. Based on neural models, the optimization process was performed with an evolutionary algorithm. The aim of the optimization was to calculate the values of independent variables that produced the maximum percent area coverage. During the optimization process, the range of independent variables was the same as that detailed in Table 1. The optimization process was performed in two different ways. Firstly, the three neural models presented in Table 3 were used. Using each of these models, only one output parameter could be optimized (PAC_{ul}, PAC_{vtl}, or PAC_{vta}). Then, the new neural model was developed, which described the relationship between the three input parameters: droplet size, driving speed, and spray angle, and the three output parameters: PAC_{ul}, PAC_{vtl}, and PAC_{vta}. The structure of the neural model was 3–14–3; the transfer functions of the neurons were sigmoidal. The coefficient of determination, R^2, values obtained for the model were as follows: 0.923 for the training, 0.923 for the test, and 0.917 for the validation

Table 4
Optimum parameters calculated for different sprayed surfaces

Optimized parameter	Droplet size	Driving speed	Spray angle	PAC_{vta}	PAC_{vtl}	PAC_{ul}
PAC_{vta}	398	3.8	20	28	1	27
PAC_{vtl}	219	1.1	–20	2	30	80
PAC_{ul}	362	1.1	0	3	5	87
$PAC_{vta} + PAC_{vtl} + PAC_{ul}$	252	1.1	–20	5	18	81

data set. Using this model, the sum of percent area coverage of all the sprayed surfaces was optimized. The results of the optimization process are detailed in Table 4. Table 4 presents optimum values of droplet size, driving speed, and spray angle calculated by a genetic algorithm based on neural models developed for each sprayed surface or for the sum of all sprayed surfaces.

Also, Table 4 shows the values of the calculated percent area coverage based on neural models for optimum process parameters. When the PAC of the vertical transverse approach surface was optimized, it was found that the droplet size should be coarse (about 400 μm), the driving speed should be high $\left(\text{about } 4\ \text{m}\cdot\text{s}^{-1}\right)$, and the spray angle should be 20°. A droplet size of around 400 μm could be produced by the twin air-induction flat-fan nozzle, AVI TWIN 11002, working at a pressure of 400 kPa. These input parameters gave low values of PAC_{vtl} and PAC_{ul}. When the PAC of the vertical transverse leaving surface was optimized, it was found that the droplet size should be fine (about 200 μm), the driving speed should be low $\left(\text{about } 1\ \text{m}\cdot\text{s}^{-1}\right)$, and the spray angle should be –20°. A droplet size of around 200 μm could be produced by the twin standard flat-fan nozzle, DG TJ60 11002, with a pressure of 400 kPa. When applying these input parameter values, PAC_{vta} gave a low value and PAC_{ul} was high. A similar input value set was calculated for optimization of the sum of PAC for all sprayed surfaces. The result was that a low PAC_{vta}, a relatively high PAC_{vtl}, and a very high PAC_{ul} were produced. The optimum PAC of the upper level surface required a droplet size of about 360 μm (which can be produced by the single air-induction flat-fan nozzle, AVI 11002, with a pressure of 400 kPa), a low driving speed $\left(\text{about } 1\ \text{m}\cdot\text{s}^{-1}\right)$, and a spray angle perpendicular to the direction of movement. An optimum PAC_{ul} value resulted in very low PAC_{vta} and PAC_{vtl}.

4. Discussion

4.1. Neural models development. In the case of mechanistic models for drift prediction presented by other researchers, discrepancies between the model and experimental values are higher than those presented in Figs. 4–6 for our models, as regards to percent area coverage prediction. This can be explained by the differences in the modeling method or the model's characteristics (input and output parameters).

Less agreement between the predicted and experimental values was reported by [25, 26] for a 3D computational fluid dynamics model and a 2D diffusion-advection model, as well as by [27] for the RTDrift model. However, these models include more input parameters and take into account some environmental parameters.

4.2. Input variables contribution determination. Our results are in agreement with [49], who reported the significant impact of nozzle type on the percent area coverage of soybean crops. Similarly, [20] found a significant ($P < 0.001$) relationship between coverage and nozzle type, as well as between coverage and pressure.

Generally, the droplet size has been noted as a very important parameter with regard to influencing spraying efficiency. The significant effect of initial droplet size on spray drift was underlined by [10]. [50] revealed that the spray drift and the pesticide residue of imidacloprid on wheat depended on the nozzle type. Good correlations between the droplet size and drift potential values were reported by [51]. [25] developed the 3D CFD model of drift depending on boom height, wind velocity, wind deviation, and injection velocity of the droplets. The accuracy of the model was quite good for near drift (<5 m) but significantly decreased at greater distances. In the year 2009 [26] presented a 2D model which was a reduction of the 3-D CFD model and produced drift prediction depending on nozzle type, wind velocity and boom height with higher accuracy ($R^2 = 0.8$). [27] presented the model of drift based on the Gaussian tilted plume model. Inputs of this model was the nozzle characteristics, nozzle position and operation parameters such as spray pressure, boom height, and wind speed.

4.3. Optimization. The results detailed in Table 4 are in agreement with other scientific reports which highlighted that spray deposition is maximized when the target is perpendicular to the droplet trajectory [52, 53]. The very high value of PAC_{ul} obtained for comparatively large droplets confirms the results reported by [54].

It can be concluded that the choice of appropriate nozzle type and spray pressure is an important aspect of protecting field and garden crops, as was previously pointed out by [55].

5. Conclusions

Artificial neural networks are a useful tool for the development of accurate mathematical models of the relationships between the percent area coverage of sprayed surfaces and droplet size (affected by nozzle type and spray pressure), driving speed, as well as spray angle. Based on neural models, the relative importance of explanatory variables can be calculated. The droplet size has the highest influence on all output parameters: the PAC of the upper level surface, the vertical transverse approach surface, and the vertical transverse leaving surface. A significantly lower impact was calculated for the driving speed and spray angle. An increase in the vertical transverse approach surface coverage can be obtained by high driving speed when the nozzles are angled forward. Conversely, an increase in the vertical transverse leaving surface coverage requires a low driving speed and nozzles angled backward. The authors found that a higher PAC of the upper level surface is obtained for single flat-fan nozzles, while twin nozzles cover vertical surfaces better, which is in agreement with previous studies. Improving pesticide application efficiency is crucial for both the economic and environmental aspects of crop protection. Therefore, the optimization of spray application parameters is of very high importance. Adequate neural models can be used for the optimization process, based for example on an evolutionary algorithm. This method can calculate a set of process parameters that produces maximum coverage, not only for one sprayed surface, but also for the sum of all sprayed surfaces. This approach is of limited use where the spray process parameters are very different from those in the data set used for the ANN training. However, the methodology presented in this work can be used for the development of mathematical models describing spray application processes based on data from experiments under field conditions. These models can include the effect of variability in environmental parameters, and therefore can provide optimum spraying process parameters valuable in real-world applications. This study can provide guidance on the proper and optimal application of pesticides.

References

[1] EP, European Parliament, November 24, 2009. Directive 2009/128/EC of the European Parliament and of the Council of 21 October 2009 establishing a framework for co mmunity action to achieve the sustainable use of pesticides. Available at: http://eurlex.europa.eu/legal-content/EN/TXT/?qid=1480964412858&uri=CELEX:32009L0128 2009, accessed 1 December 2016.

[2] A. Özkara, D. Akyıl, and M. Konuk, "Pesticides, Environmental Pollution, and Health," *Environmental Health Risk – Hazardous Factors to Living Species*, 2016.

[3] P. Nicolopoulou-Stamati, S. Maipas, C. Kotampasi, P. Stamatis, and L. Hens, "Chemical Pesticides and Human Health: The Urgent Need for a New Concept in Agriculture", *Front Public Health* 4,148 (2016).

[4] K. Sabanci and K. Aydin, "Smart robotic weed control system for sugar beet", *J. Agr. Sci. Tech*. 19, 73–83 (2017).

[5] J.C. Ferguson, R.G. Chechetto, C.C. O'Donnell et al., "Determining the drift potential of Venturi nozzles compared with standard nozzles across three insecticide spray solutions in a wind tunnel", *Pest Manag. Sci.* 72, 1460–1466 (2016).

[6] C.E. Atay, and P. Ayebare, "Determination of buffer-zones using agricultural information system", *TEM Journal.* 6, 363–371 (2017).

[7] P. Balsari, E. Gil; P. Marucco, J. C. van de Zande, D. Nuyttens, A. Herbst, and M. Gallart, "Field-crop-sprayer potential drift measured using test bench: Effects of boom height and nozzle type", *Biosyst. Eng.* 154, 3–13 (2017).

[8] E. Brusselman, B. Beck, S. Pollet et al., "Effect of the spray application technique on the deposition of entomopathogenic nematodes in vegetables", *Pest Manag. Sci*. 68, 444–453 (2012).

[9] A. Hanafi, M. Hindy, and S. A. Ghani, "Effect of spray application techniques on spray deposits and residues of bifenthrin in peas under field conditions", *J. Pestic. Sci.* 41, 49–54 (2016).

[10] C. Kjaer, M. Bruus, R. Bossi et al., "Pesticide drift deposition in hedgerows from multiple spray swaths", *J. Pestic. Sci.* 39, 14–21 (2014).

[11] D. Nuyttens, K. Baetens, M. De Schampheleire, and B. Sonck, "Effect of nozzle type, size and pressure on spray droplet characteristics", *Biosyst. Eng*. 97, 333–345 (2007).

[12] J.C. Ferguson, R.G. Chechetto, A.J. Hewitt et al., "Assessing the deposition and canopy penetration of nozzles with different spray qualities in an oat Avena sativa L. canopy", *Crop Prot*. 81, 14–19 (2016).

[13] V. Visacki, A. Sedlar, E. Gil, R. Bugarin, J. Turan, T. Janić, and P. Burg, "Effects of sprayer boom height and operating pressure on the spray uniformity and distribution model development", *Appl. Eng. Agric.* 32, 341–346 (2016).

[14] D. Foque, J.G. Pieters, and D. Nuyttens, "Effect of spray angle and spray volume on deposition of a medium droplet spray with air support in ivy pot plants", *Pest Manag. Sci*. 70, 427–439 (2014).

[15] M. De Schampheleire, D. Nuyttens, K. Baetens, W. Cornelis, D. Gabriels, and P. Spanoghe, "Effects on pesticide spray drift of the physicochemical properties of the spray liquid", *Precis. Agric.* 10, 409–420 (2009).

[16] T. Arvidsson, L. Bergstrom, and J. Kreuger, "Spray drift as influenced by meteorological and technical factors", *Pest Manag. Sci.* 67, 586–598 (2011).

[17] R.C. Derksen, H.E. Ozkan, P.A. Paul, and H. Zhu, "Plant canopy characteristics effect on spray deposition", *Asp. Appl. Biol.* 122, 227–235 (2014).

[18] W.I.W. Ishak, R.M. Hudzari, and M.M.N Ridzuan, „Development of variable rate sprayer for oil palm plantation", *Bull. Pol. Ac.: Tech.* 59, 299–302 (2011).

[19] M. Cunha, C. Carvalho, and A.R.S. Marcal, "Assessing the ability of image processing software to analyse spray quality on water-sensitive papers used as artificial targets", *Biosyst. Eng.* 111, 11–23 (2012).

[20] J.C. Ferguson, A.J. Hewitt, and C.C. O'Donnell, "Pressure, droplet size classification, and nozzle arrangement effects on coverage and droplet number density using air-inclusion dual fan nozzles for pesticide applications", *Crop Prot*. 89, 231–238 (2016).

[21] M. Sies, F.N. Madzlan, N Asmuin, A. Sadikin, and H Zakaria, "Determine spray droplets on water sensitive paper (WSP) for low pressure deflector nozzle using image J" *IOP Conference Series: Materials Science and Engineering,* p. 243, 2017.

[22] J. Sanchez-Hermosilla, V.J. Rincon, F. Paez, and M. Fernandez, "Comparative spray deposits by manually pulled trolley sprayer and a spray gun in greenhouse tomato crops", *Crop Prot.* 31, 119–124 (2012).

[23] J.T. Witton, M.D. Pickering, T. Alvarez, M. Reed, G. Weyman, M.E. Hodson, and R. Ashauer, "Quantifying pesticide deposits and spray patterns at micro-scales on apple (Malus domesticus) leaves with a view to arthropod exposure", *Pest. Manag. Sci*. 74, 2884–2893 (2018).

[24] P. Lofstrom, M. Bruus, H.V. Andersen, C. Kjaer, D. Nuyttens, and P. Astrup, "The OML-SprayDrift model for predicting pesticide drift and deposition from ground boom sprayers", *J. Pestic. Sci.* 38, 129–138 (2013).

[25] K. Baetens, D. Nuyttens, P. Verboven, M. De Schampheleire, B. Nicolaï, and H. Ramon, „Predicting drift from field spraying by means of a 3D computational fluid dynamics model", *Comput. Electron. Agric.* 56, 161–173 (2007).

[26] K. Baetens, Q.T. Ho, D. Nuyttens et al., A validated 2-D diffusion-advection model for prediction of drift from ground boom sprayers, *Atmos. Environ*. 43, 1674–1682 (2009).

[27] F. Lebeau, A. Verstraete, C. Stainier, and M.F. Destain, "RTDrift: A real time model for estimating spray drift from ground applications", *Comput. Electron. Agric*. 77, 161–174 (2011).

[28] M.C. Kennedy, M.C.B. Ellis and P.C.H. Miller "BREAM: A probabilistic Bystander and Resident Exposure Assessment Model of spray drift from an agricultural boom sprayer", *Comput. Electron. Agric*. 88, 63–71 (2012).

[29] K. Pentoś and K. Pieczarka, "Applying an artificial neural network approach to the analysis of tractive properties in changing soil conditions". *Soil Tillage Res.* 165, 113–120 (2017).

[30] P. Braekman and B. Sonck, "An appropriate technical inspection methodology to tackle the great diversity of spray equipment used in Flemish greenhouses", *Asp. Appl. Biol*. 83, 95–98 (2007).

[31] P. Braekman and B. Sonck, "A review of the current spray applications techniques in various ornamental plant production systems in Flanders, Belgium", *Asp. Appl. Biol*. 84, 303–308 (2008).

[32] D. Ghosh, U.P. Singh, K. Ray, A. Das, "Weed management through herbicide application in direct-seeded rice and yield modeling by artificial neural network", *Span. J. Agric. Res*. 14, e1003, 2016.

[33] L. Johann, A. G. de Araújo, H.C. Delalibera, and A.R. Hirakawa, "Soil moisture modeling based on stochastic behavior of forces on a no-till chisel opener", *Comput. Electron. Agric*. 121, 420–428 (2016).

[34] C.T. Kowalski and M. Kamiński, "Rotor fault detector of the converter-fed induction motor based on RBF neural network", *Bull. Pol. Ac.: Tech.* 62, 69–76 (2014).

[35] X. Li, F. Chen, D. Sun, and M. Tao, "Predicting menopausal symptoms with artificial neural network", *Expert Syst. Appl.* 42, 8698–8706 (2015).

[36] N.S. Reddy, B.B. Panigrahi, C.M. Ho, J.H. Kim, and C.S. Lee, "Artificial neural network modeling on the relative importance of alloying elements and heat treatment temperature to the stability of alpha and beta phase in titanium alloys", *Comput. Mater. Sci.* 107, 175–183 (2015).

[37] S. Tohidi and Y. Sharifi, "Neural networks for inelastic distortional buckling capacity assessment of steel I-beams", *Thin-Walled Struct.*, 94, 359–371 (2015).

[38] A.J. Malekabadi, M. Sadeghi, and H.Z. Dizaji, "Comparing Quality of a Telescopic Boom Sprayer with Conventional Orchard Sprayers in Iran", *J. Agr. Sci. Tech*. 18, 585–599 (2016).

[39] ANSI/ASABE. Spray Nozzle Classification by Droplet Spectra. Standard 572.1 American Society of Agricultural and Biological Engineers, St. Joseph, MI, 2009.

[40] S. Agatonovic-Kustrin and R. Beresford, "Basic concepts of artificial neural network ANN modeling and its application in pharmaceutical research", *J. Pharm. Biomed. Anal*. 22, 717–727 (2000).

[41] J.E. Madden, N. Avdalovic, P.R. Haddad, and J. Havel, "Prediction of retention times for anions in linear gradient elution ion chromatography with hydroxide eluents using artificial neural networks". *J Chromatogr. A* 910, 173–179 (2001).

[42] M. Gevrey, L. Dimopoulos, and S. Lek, "Review and comparison of methods to study the contribution of variables in artificial neural network models", *Ecol Modell*, 160, 249–264 (2003).

[43] K. Pentoś, "The methods of extracting the contribution of variables in artificial neural network models – Comparison of inherent instability", *Comput. Electron. Agric*.127, 141–146 (2016).

[44] R. Barati, "Application of excel solver for parameter estimation of the nonlinear Muskingum models", *Ksce J. of Civ. Eng*. 17, 1139–1148 (2013).

[45] R.K. Bhattacharjya, "Solving Groundwater Flow Inverse Problem Using Spreadsheet Solver", *J. Hydrol. Eng.* 16, 472–477 (2011).

[46] S.M. Lee and A.A. Asllani, "Job scheduling with dual criteria and sequence-dependent setups: mathematical versus genetic progra mming", *Omega-Int. J. Manage. Sci.* 32, 145–153 (2004).

[47] M.A. Mazurowski and P.M. Szecówka, "Limitations of sensitivity analysis neural networks in cases with dependent inputs", in *IEEE International Conference on Computational Cybernetics* pp. 1–5, 2006.

[48] P.M. Szecowka, A. Szczurek, and B.W. Licznerski, "On reliability of neural network sensitivity analysis applied for sensor array optimization", *Sens. Actuator B-Chem*. 157, 298–303 (2011).

[49] R.E. Wolf, and N.P. Daggupati, "Nozzle type effect on soybean canopy penetration", *Appl. Eng. Agric*. 25, 23–30 (2009).

[50] H.Y. Zhao, C. Xie, F.M. Liu, X.K. He, J. Zhang, and J.L. Song, "Effects of sprayers and nozzles on spray drift and terminal residues of imidacloprid on wheat", *Crop Prot*. 60, 78–82 (2014).

[51] E. Gil, P. Balsari, M. Gallart, et al. "Determination of drift potential of different flat fan nozzles on a boom sprayer using a test bench", *Crop Prot.* 56, 58–68 (2014).

[52] R.H. Elliott and L.W. Mann, "Control of wheat midge, Sitodiplosis mosellana Gehin, at lower chemical rates with small-capacity sprayer nozzles", *Crop Prot*. 16, 235–242 (1997).

[53] B. Richardson and M. Newton, "Spray deposition within plant canopies", *N. Z. Plant Prot*. 53, 248–252 (2000).

[54] L.E. Bode, "Spray application technology", in *Methods of Applying Herbicides*. WSSA Monograph 4 ed., pp. 85–110 eds. G. McWorter and M.R. Gebhardt, Weed Science Society of America, Champaign Illinois, USA, 1987.

[55] H. Zhu, R.C. Derksen, H. Guler, C.R. Krause, and H.E. Özkan, "Foliar deposition and off-target loss with different spray techniques innursery applications", *T ASABE* 49, 325–333 (2006).