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ESTIMATION OF LONGITUDINAL PRECIPITATION OF LIQUID INDICATOR (LPLI) WITH THE USE OF THE ARTIFICIAL NEURAL NETWORK (MLP, RBF) MODELS

Summary

The study presents the results of the analysis of two artificial neural networks as models of relationships between longitudinal precipitation of liquid indicator and selected technical and technological factors of spraying process. The measurements were conducted in laboratory conditions. A wind tunnel was primary element in experimental set-up. Based on the results, it can be stated that MLP model (R^2 = 0.908 for validation data set) was more accurate that RBF model (R^2 = 0.837 for validation data set). The analysis of input variables' contribution indicated that the LPLI is influenced the most by the air flow speed and the droplet size. Spray boom height and spray nozzle angle were less influencing parameters.
***Key words**: spraying efficiency, artificial neural network, longitudinal precipitation*

ESTYMACJA WSKAŹNIKA OPADU PODŁUŻNEGO ROZPYLONEJ CIECZY (Wso) ZA POMOCĄ SZTUCZNYCH SIECI NEURONOWYCH (MLP I RBF)

Streszczenie

W pracy przedstawiono wyniki analizy dwóch modeli matematycznych zależności między wskaźnikiem opadu podłużnego rozpylonej cieczy a wybranymi technicznymi i technologicznymi parametrami procesu opryskiwania. Modele zbudowano wykorzystując sztuczne sieci neuronowe. Pomiary przeprowadzono w warunkach laboratoryjnych. Głównym elementem stanowiska badawczego był tunel aerodynamiczny. Na podstawie otrzymanych wyników można stwierdzić, że model oparty o sieć MLP (R^2 = 0.908 dla zbioru walidacyjnego) charakteryzował się wyższą dokładnością niż model oparty o sieć RBF (R^2 = 0.837 dla zbioru walidacyjnego). Analiza stopnia wpływu poszczególnych parametrów wejściowych modelu na jego wyjście wskazuje, że największy wpływ na Wso mają prędkość przepływu powietrza oraz wielkość kropli. Wysokość belki opryskowej oraz kąt nachylenia rozpylacza w znacznie mniejszym stopniu wpływają na Wso.
***Słowa kluczowe**: jakość opryskiwania, sztuczne sieci neuronowe, rozkład podłużny*

1. Introduction

Liquid atomization has significant influence on spray application process especially in terms of chemical methods of plant protection. Primary objective of this process is to increase the deposition of atomised liquid on the plant surface. It is known, that spraying is one of the most difficult stages of plant production. Forster et al. [5, 6] indicate that the spraying process consists of the following stages:

- deposition (the amount of plant protection products that has reached the target area and which was the result of drift),
- stopping (the number of droplets that reached the destination - in case of crops, weeds or pests),
- absorption (spray absorbed by plant leaves),
- translocation (amount of absorbed material transferred to the site of biological activity).

If one of the stages happens less efficient, this situation may cause economic loss, environmental pollution, deterioration of food safety, and reduction of biological efficiency [21]. Besides, there are a lot of factors which must be taken into account: the physical and chemical properties of liquid used, atmospheric conditions, as well as technical and technological parameters [14, 16, 19]. The quality of spraying process is determined on the basis of one of three indicators: distribution of precipitation of spray liquid, degree of coverage of sprayed objects and deposition of spray liquid. Experiments, which were conducted in terms of precipitation of spray liquid, are mainly tests of transverse distribution liquid. The research on longitudinal liquid precipitation are conducted comparatively rarely, due to the difficulty in carrying out such experiments.

Mathematical models can be used to understand better the relationships between technical and environmental parameters and spray application efficiency. Several mechanistic models of spray drift prediction have been proposed in literature: the OML-SprayDrift model [13], a 3Dfully mechanistic model [2], and a Gaussian plume model [11]. In the case of difficulties in mechanistic model development, artificial intelligence methods, such as artificial neural networks (ANNs), can be used to produce sufficiently accurate models. The most popular ANNs for modeling are Multilayer Perceptron (MLP) and Radial Basis Function (RBF). These techniques were widely used for modeling in agricultural applications: by Ghosh et al. [7] for yield modeling, by Johann et al. [8] for soil moisture modeling, by Kashi et al. [9] for estimation of soil infiltration and cation exchange capacity, and by Wang et al. [20] for monitoring nitrogen concentration of oilseed rape.

Taking into account that there is still a need for the improvement of spray application techniques, it is worth to emphasize that ANN techniques can give information about the predictor variables' importance [12] and can be used as an objective function in the optimization process [18].

The objectives of the present study was to develop the two ANN models (MLP and RBF) of the relationships between longitudinal precipitation of liquid indicator and nozzle type, spray pressure, air flow speed, as well as spray angle and spray boom height. Based on MLP model, the input variables' importance was determined.

2. Methodology
2.1. Experimental set-up

The following parameters of nozzles' work were used for the research:
- spray boom height h – 0.5; 0.6 m,
- liquid's pressure p – 0.2; 0.3; 0.4 MPa,
- air flow speed v_w – 0; 1.5; 3.0; 4.5; 6.0 $m \cdot s^{-1}$,
- set nozzle in a longitudinal plane, perpendicular to the ground – 0°; 5°; 15°; 25°,
- nozzles: dual stream standard DF, air injector IDKT.

Experiments on the sprayed liquid distribution were conducted on the experimental set-up presented in Fig. 1. An aerodynamic tunnel was a primary element of the research stand. A tube straightener was used for the uniformization of the air flow in wind tunnel. The nozzle was mounted on the stand in the aerodynamic tunnel. The stand made it possible to change the spraying height. The nozzle was placed in a holder that allowed the spray angle to be adjusted relative to the substrate and axis of the air duct. The air flow was generated by the axial fan, while the speed fan was controlled by changing the cross-sectional area of the inlet port. The sprayed surface was a groove table.

Droplet size was measured on a spectral laser analyzer "Spraytec" by Malvern Instruments and results are detailed in Table 1.

Table 1. Characteristics of the nozzles used in the research
Tab. 1. Charakterystyka rozpylaczy użytych w badaniach

Nozzle	Pressure [MPa]	Droplet size [μm]
DF	0.2	127
DF	0.3	117.8
DF	0.4	110.5
IDKT	0.2	553.6
IDKT	0.3	439.8
IDKT	0.4	395.3

Source: own work / Źródło: opracowanie własne

In order to determine the longitudinal precipitation of liquid indicator (LPLI), the following formula was used:

$$LPLI = \frac{\sum V_i}{V_c} \cdot 100\% \qquad (1)$$

Vi - the sum of the liquid volume from the sprayed surface,
Vc - the total volume of liquid used for the measurement.

2.2. Artificial neural network development

ANNs are composed of simple processing elements - artificial neurons, which are arranged in layers. The most popular ANN architecture is MLP, also called a feed-forward network. MLP is trained using one of the supervised learning algorithms. An MLP used in this research comprises three layers: an input layer, a hidden layer, and an output layer. The function of the input layer is to map the input vector directly to the hidden layer. Neurons in hidden layer process input parameters based on weights and biases values as well as transfer function. The most popular transfer functions in MLP networks are sigmoidal and hyperbolic tangent. Neurons in output layer produce output signal of MLP model from signals generated in hidden layer. The MLP training process includes the presentation of training data set vectors to network, calculation of network errors, and updating the weights and biases. RBF, similarly to MLP, is a kind of feed-forward neural network. It is formed of three layers: an input layer, always only one hidden layer, and output layer. The function of RBF input layer is analogous to MLP. In hidden layer, unsupervised training component is involved during training process. The transfer function of neurons in hidden layer is a radial activated function, and the output neurons implement a weighted sum of hidden neurons outputs. The RBF training process includes adjustment of centers and spreads of radial activated function as well as weights of output neurons.

The number of neurons in the ANN hidden layer significantly influences the model's quality, and is set by a trial and error approach. Therefore, the number of neurons in the hidden layer of both, MLP and RBF, was set to a range of 10 to 40. The experimental data set containing 240 data vectors was randomly separated into training, test, and validation sets in a 70:15:15 ratio.

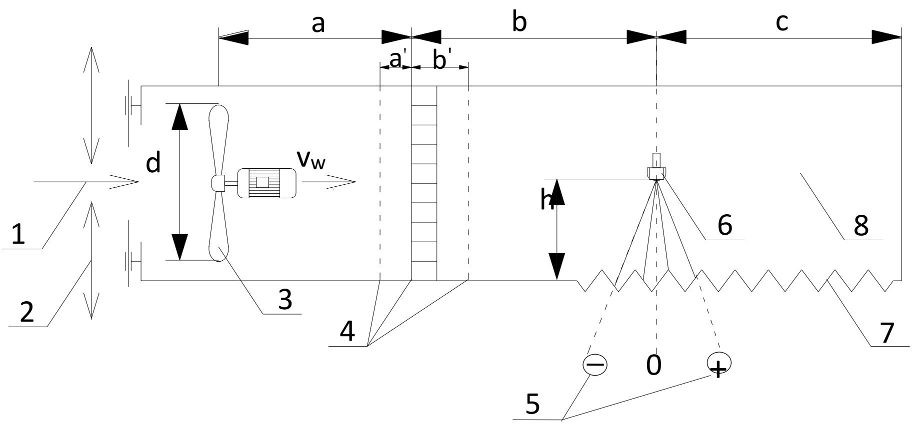


Fig. 1. Scheme of the experimental set-up for the research on the distribution of the sprayed liquid fall in conditions [19]
Rys. 1. Schemat stanowiska pomiarowego do badań rozkładu podłużnego opadu rozpylonej cieczy [19]

The data were normalized into a range a range of 0 to 1. Simulations were performed using *Statistica 10* software. The transfer functions of the neurons in MLP hidden and output layers were as follows: sigmoidal, hyperbolic tangent, and exponential. The transfer functions of the neurons in RBF hidden layer were Gaussian distribution. For MLP model, the 1000 independent ANNs were trained. In the case of RBF model, the 500 independent ANNs were trained. Model quality assessment was based on the values of two indicators, the coefficient of determination (R^2) and the mean square error (MSE).

2.3. Methods for quantifying variable importance

ANN models of high accuracy can be used to determine the contribution of each independent input variable. In this research, the sensitivity analysis implemented in *Statistica 10* was used for this purpose. For various reasons, it is difficult to select the optimal ANN model, and results of sensitivity analysis based on single ANN model can be misleading [17]. Therefore, quantifying variable importance was conducted based on the group of twenty MLP models with the highest R^2 and the lowest MSE value. As the final result, the arithmetical mean of the results produced by the twenty ANNs was calculated.

3. Results and discussion

3.1. Neural models development

It is worth to emphasize that development of an ANN model with linearly dependent input parameters is a methodological mistake. Furthermore, methods of the investigation of the inputs relative contribution based on that model can produce unreliable results [15]. Therefore, the Pearson's correlation coefficients between the explanatory variables were calculated and results are presented in Table 2.

The data presented in Table 2 show that the correlation coefficients between the input variables are very low, therefore they can be used for neural model development.

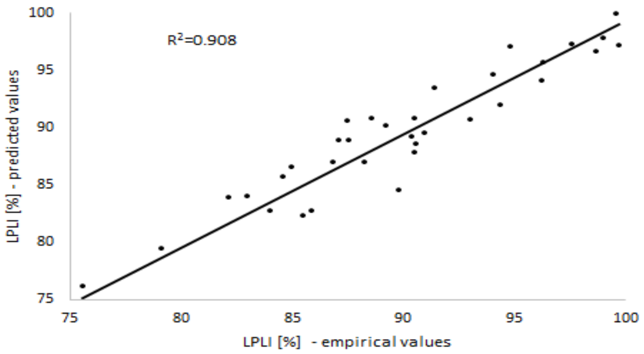
3.2. Multilayer Perceptron model

During simulations, the group of 1000 ANN-MLP structures was trained with the data set. The following parameters were different in each ANN structure: the number of neurons in the hidden layer, the initial connection weight vectors, the training algorithm, and the transfer functions of the neurons in the hidden and output layer. The parameters of the best ANN architecture are detailed in Table 3. The MSE values were calculated for normalized data.

Table 2. Correlation coefficients between explanatory variables ($p < 0.05$)
Tab. 2 Współczynniki korelacji liniowej Pearsona dla zmiennych niezależnych ($p < 0.05$)

	Droplet size	Spray boom height	Spray angle	Air flow speed
Droplet size	1.00	0.01	0.01	0.01
Spray boom height	0.01	1.00	0.01	0.01
Spray angle	0.01	0.01	1.00	0.01
Air flow speed	0.01	0.01	0.01	1.00

Source: own work / Źródło: opracowanie własne



Source: own work / Źródło: opracowanie własne

Fig. 2. Predicted values versus measured values of LPLI (validation data set, MLP model)
Rys. 2. Wartości Wso uzyskane z modelu i z pomiarów (walidacyjny zbiór danych, model MLP)

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 value of R^2 higher than 0.90 calculated for validation data set means that no overfitting effect occurred during training process and the ANN model has a high generalization ability. Therefore, this model can be used for practical applications.

Fig. 2 depicts the performance of the MLP model predicted values of the LPLI vs. the measured values in the validation set.

Table 3. The parameters of the best ANN structure used as MLP neural model
Tab. 3. Parametry najlepszej sieci MLP

ANN structure	Coefficient of determination R^2			Mean square error		
	training data set	test data set	validation data set	training data set	test data set	validation data set
4-20-1	0.925	0.931	0.908	0.002	0.002	0.002

Source: own work / Źródło: opracowanie własne

Table 4. The parameters of the best ANN structure used as RBF neural model
Tab. 4. Parametry najlepszej sieci RBF

ANN structure	Coefficient of determination R^2			Mean square error		
	training data set	test data set	validation data set	training data set	test data set	validation data set
4-13-1	0.737	0.758	0.837	0.006	0.006	0.003

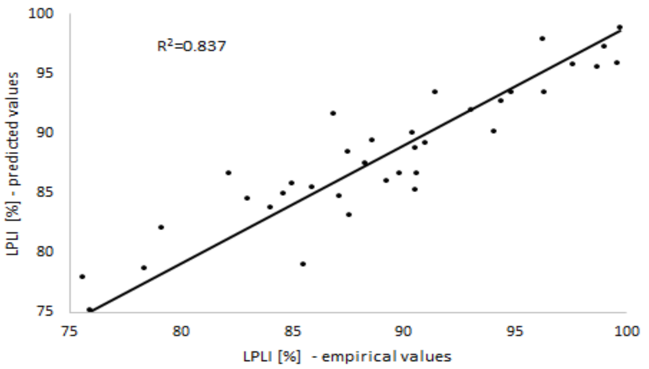
Source: own work / Źródło: opracowanie własne

3.3. Radial Basis Function network model

When the RBF ANN model was developed, the group of 500 ANN structures with different number of neurons in hidden layer was trained with the data set. The parameters of the best ANN-RBF architecture are presented in Table 4. The MSE values were calculated for normalized data.

As shown in Table 4, RBF model produced slightly lower values of R^2 and higher values of MSE for the training, test, and validation data sets comparing to MLP model. In the case of validation data set, the R^2 value is higher than 0.83. It can be stated that RBF model also has a high generalization ability and can be used for practical applications. In Fig. 3, the performance of the RBF model predicted values of the LPLI vs. the measured values in the validation set is presented.

In the literature, some mechanistic models for drift prediction can be found [2, 11]. The discrepancies between the values predicted by the model and experimental values are higher than those obtained in our work with the use of MLP and RBF models. However, models presented by in [2, 11] include more input parameters and take into account some other environmental parameters.



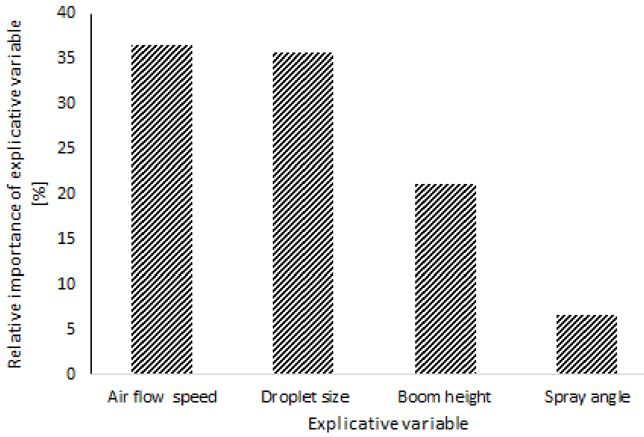
Source: own work / Źródło: opracowanie własne

Fig. 3. Predicted values versus measured values of LPLI (validation data set, RBF model)
Rys. 3. Wartości Wso uzyskane z modelu i z pomiarów (walidacyjny zbiór danych, model RBF)

Results obtained in our work show better accuracy of MLP model. Similar results were shown by Kashi et al. [9] for soil infiltration and cation exchange capacity estimation. In their research, R^2 values for validation data set were 0.97 for MLP and 0.86 for RBF in the case of infiltration.. For cation exchange capacity they obtained $R^2 = 0.89$ for MLP and $R^2 = 0.74$ for RBF. Opposite results were reported by Johann et.al [8] for soil moisture modeling. Higher R^2 value (0.80) was obtained for validation data set for RBF 6-25-1 than for MLP 6-8-1 (0.79). However, the difference is very low and models developed by Johann et.al [8] show lower accuracy that models developed in our research.

3.4. Input variables contribution determination

An analysis of the independent input variables' contributions was carried out, based on the group of 20 the best ANNs chosen from the 1000 MLP models that were developed during the training process. The selection criterion was the highest R^2 value and the lowest MSE value calculated for the validation data set. The number of neurons in the hidden layer was in the range of 10 to 40. The R^2 values were between 0.868 and 0.908. The results of the relative importance of the input parameters are presented in Fig. 4. As illustrated in Fig. 4, the air flow speed and the droplet size, which was affected by the type and pressure of nozzles, had the highest influence on LPLI values (more than 35%). Lower influence was calculated for spray boom height (21.23%). Spray angle affects the LPLI only in 6.63%. Our results are in good agreement with those of other researchers. High influence of air flow speed on spray drift was reported by Arvidsson et al. and Carlsen et al. [1, 3]. Also the droplet size was indicated as a very important parameter with regard to influencing spraying efficiency what was underlined by Kjaer et al. and Zhao et al. [10, 22]. Significantly lower impact was observed in the case of spray angle what was reported by Foque et al. [4].



Source: own work / Źródło: opracowanie własne

Fig. 4. Effect of independent variables in LPLI model
Rys. 4. Wpływ zmiennych niezależnych modelu na Wso

4. Conclusions

Many parameters influence the quality of spraying process. In this work, the longitudinal precipitation of liquid was chosen as the indicator of spraying efficiency. The measurements were conducted in laboratory conditions and five parameters affected the LPLI: nozzle type, spray pressure, air flow speed, spray angle, and spray boom height. In further analysis nozzle type and spray pressure were represented by droplet size. Two mathematical models based on artificial neural networks were developed: MLP and RBF. Both models were of high accuracy and can be used in real world applications. However, a little higher R^2 values and lower MSE values were calculated for MLP model. Based on sensitivity analysis of MLP model it can be concluded that LPLI is affected the most by air flow speed and the droplet size. The influence of spray boom height and spray angle is significantly lower.

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