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APPLICATION OF SOYBEAN OIL AND GLYCEROL IN ANIMAL FEED PRODUCTION, ANN MODEL

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In the past few decades the diet preparation in feed production has evolved towards more complicated technological operations, which include different liquid addition. A wide scale of different liquids is used in contemporary animal feed production, from oils and glycerol to more expensive products in a liquid form, such as enzymes, flavourings, amino acids, vitamins and others. In the presented study the liquid addition in feed production was observed, with a specific goal to investigate the spraying systems in order to better understand the effects of fluids, such as soybean oil and glycerol, on feed production. The dispersion angles of spraying nozzle for glycerol and soybean oil were determined as an indicator of the uniform application of liquids during feed production. Dispersion of the material was accomplished using the two-fluid nozzle. The performance of Artificial Neural Network (ANN) was compared with experimental data in order to develop rapid and accurate method for prediction of dispersion angle. The ANN model showed high prediction accuracy (r^2 = 0.945).

Keywords: liquid addition, nozzle, spray pattern, dispersion, ANN

INTRODUCTION

Liquid application in feed production is highly sensitive and important step, since its application to feedstuffs influences technological quality, taste and nutritional value of produced feed, decreases the dust and prevent the segregation of the material (1). In the past few decades, diet preparation has evolved from simple mixing operation towards more advanced thermal technological operations such as pelleting, expanding and extruding (2). Nevertheless, thermal treatments have a negative impact on heat sensitive additives, therefore, the post-pellet liquid application (PPLA), which can be combined with vacuum coating, or separately, is very suitable for bioactive protection (3). The PPLA has many advantages such as: application of different liquids on extrudates, possibility of addition of higher level of liquids with minimal destruction of feed structure and the possibility of different liquid mixing before their addition on the extrudates (4).

The post-pelleting application of oil can enhance the quality of extrudates due to improved elasticity of the extrudates by higher fat or oil inclusion (5). Additionally, it can improve the energy value of the produced extrudates and there is the possibility of adding various bioactive liquids along with fat (3). Glycerol could also improve the energy value of the feed, as a good replacement for corn grain (6). Furthermore, glycerol is used in a pet food industry as a binder and sweetener for canned foods in order to improve the chewiness and taste (7).

Lipid oxidation is a problem frequently encountered in the storage of feed rich in fats, especially with the high polyunsaturated fatty acids (PUFA) content. It causes the forma-

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tion of highly reactive products, whose presence in feed has a negative impact on animal health and can be the reason for the deterioration of the nutritional quality and sensory characteristics of feed. Additionally, thermal processing of feeds usually reduces their oxidative stability (8). Thereby, one of the important aspects of the PPLA process is described as an opportunity to improve bioavailability of bioactive sensitive to oxidation and shelf-life of produced feed (3).

Proper selection of a nozzle type and size in PPLA is essential for uniformity of liquid additive application and coverage obtained on the target surface (9). There are a lot of different commercially available nozzles that can be used to obtain the desirable spray pattern and spray angle, as an indicator of accurate and correct application of liquids. Two-fluid nozzle is suitable for various solvent-based solutions, which contained coating polymer (10). The mechanism of work of the two-fluid nozzle is based on the liquid injection into the high-velocity airstream creating high frictional forces over liquid surfaces leading to fragmentation of liquid into spray droplets (11).

Artificial Neural Network (ANN) modeling has already been used in the estimation and prediction of food properties such as prediction of antyoxidative activite in food systems (12). Recently, ANN has been increasingly used for the study of the given systems. Additionally ANN models have gained momentum for modelling of spraying nozzle (13, 14). ANN models are recognized as a good modelling tool since they provide the empirical solution to the problems from a set of experimental data, and are capable of handling complex systems with nonlinearities and interactions between decision variables (15). The developed empirical models show a reasonable fit to experimental data and successfully predict dispersion angles of spraying nozzle for glycerol and oil (16, 17). These studies support the view that nonlinear models are more suitable for real process simulation.

Spraying systems are still not well investigated in the field of animal feed science. Therefore, the aim of the presented research was to investigate the spraying systems in order to better understand the behavior of different liquid additives during feed production. The performance of the ANN was compared with the experimental data in order to develop rapid and accurate method for prediction of dispersion angles of spraying nozzle for two types of fluids: glycerol and soybean oil.

EXPERIMENTAL

Two-fluid nozzle (Schlick Model 970-S1, Germany) was used for distributing glycerol (Gram, Serbia) and soybean oil (Victoriaoil, Serbia). The operational conditions were planned according to full factorial experimental design with three levels and two parameters (temperature and nozzle diameter) and two types of fluids. This design was chosen because it does not include combinations of parameters in which all factors are at highest or lowest levels 18). The effects of temperature and nozzle diameter, and fluid type on the dispersion angles of spraying nozzle for glycerol and soybean oil were performed according to Dragojlović et al.(19).

Artificial Neural Network (ANN) modelling

The experimental data set was used to test the performance of the developed ANN, while the network training was in progress as an indicator of the level of generalization and the time at which the network has begun to over-train.

To improve the behaviour of the ANN, both input and output data were normalized, according to the following scheme:

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$$\bar{Q} = \frac{Q - Q_{\min}}{Q_{\max} - Q_{\min}} \qquad [1]$$

where Q, $\bar{Q}$, $Q_{\min}$ and Q_{max} and are the measured value, the normalized, minimum and maximum of the input and output values, respectively

In order to obtain good network behaviour, it is necessary to make a trial and error procedure and also to choose the number of hidden layers, and the number of neurons in hidden layer(s) (20). A multi-layer perceptron model (MLP) consisted of three layers (input, hidden and output). Such a model has been proven as a quite capable of approximating nonlinear functions (21) giving the reason for choosing it in this study. In this work the number of hidden neurons for optimal network was ten. The Broyden-Fletcher-Goldfarb-Shanno (BFGS) gradient descent algorithm was used for ANN training.

The coefficients associated with the hidden layer (weights and biases) were grouped in matrices W_1 and B_1. Similarly, coefficients associated with the output layer were grouped in matrices W_2 and B_2. It is possible to represent the ANN by using matrix notation (Y is the matrix of the output variables, f_1 and f_2 are transfer functions in the hidden and output layers, respectively, and X is the matrix of input variables) (22):

$$Y = f_1(W_2 \cdot f_2(W_1 \cdot X + B_1) + B_2) \qquad [2]$$

Weights (elements of matrices W_1 and W_2) were determined during the ANN learning cycle, which updated them using optimisation procedures to minimise the error between network and experimental outputs (23,24), according to the sum of squares (SOS) and BFGS algorithm, used to speed up and stabilise convergence (25). The coefficients of determination were used as parameters to check the performance of the obtained ANN model.

Training, testing and system implementation

After defining the architecture of ANN, the training step was initiated. The training process was repeated several times in order to get the best performance of the ANN, due to a high degree of variability of parameters. It was accepted that the successful training was achieved when learning and cross-validation curves (Sum of Squares (SOS) vs. training cycles) approached zero. Testing was carried out with the best weights stored during the training step. Coefficient of determination (r^2) and SOS were used as parameters to check the performance (*i.e.* the accuracy) of the obtained ANNs.

The ANN with the best performance was chosen, the model was implemented using an algebraic system of equations to dispersion angles of spraying nozzle for glycerol and soybean oil.

The accuracy of the models

The numerical verification of the developed models was tested using coefficient of determination (r^2), reduced chi-square (χ^2), mean bias error (MBE), root mean square error (RMSE) and mean percentage error (MPE). These commonly used parameters can be calculated as follows (26):

$$\chi^2 = \frac{\sum_{i=1}^{N} (x_{\exp,i} - x_{pre,i})^2}{N - n}, \qquad [3]$$

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$$RMSE = \left[\frac{1}{N} \cdot \sum_{i=1}^{N} (x_{pre,i} - x_{\exp,i})^2 \right]^{1/2}, \quad [4]$$

$$MBE = \frac{1}{N} \cdot \sum_{i=1}^{N} (x_{pre,i} - x_{\exp,i}), \quad [5]$$

$$MPE = \frac{100}{N} \cdot \sum_{i=1}^{N} \left(\frac{\left| x_{pre,i} - x_{\exp,i} \right|}{x_{\exp,i}} \right) \quad [6]$$

where $x_{exp,i}$ stands for the experimental values and $x_{pre,i}$ are the predicted values calculated by the model for these measurements. N and n are the number of observations and constants, respectively.

RESULTS AND DISCUSSION

The experimental results of dispersion angles of spraying nozzle for glycerol and soybean oil are presented in Table 1. Dispersion angles varied significantly, implying that fitting of the experimental data can be performed using ANN modelling.

Table 1. Results of dispersion angles of spraying nozzle for glycerol and oil (n = 9 runs, for two fluids)

Temperature [°C]	Nozzle diameter [mm]	Angle [°]	
		Glycerol	Soybean Oil
40	1	17.54	29.73
40	3	24.77	33.76
40	5	33.32	35.21
50	1	28.90	30.59
50	3	31.45	33.64
50	5	32.30	37.48
60	1	38.78	38.42
60	3	37.08	36.29
60	5	34.21	24.23

Neurons in the ANN hidden layer

Determination of the appropriate number of hidden layers and the number of hidden neurons in each layer is one of the most critical tasks in the ANN design. The number of neurons in a hidden layer depends on the complexity of the relationship between inputs and outputs. As this relationship becomes more complex, more neurons should be added (27).

The optimum number of hidden neurons was chosen upon minimizing the difference between predicted ANN and experimental values, using Sum of Squares (SOS) during testing as a performance indicator. Used multi-layer perceptron models (MLPs) were marked according to StatSoft Statistica's notation. MLP was followed by a number of inputs, number of neurons in the hidden layer, and the number of outputs. According to ANN performance (Table 2), the optimal number of neurons in the hidden layer for dis-

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persion angles of spraying nozzle for glycerol and the soybean oil calculation was 9 (network MLP 3-9-1). Obtained ANN has a high values of r^2 (0.972) and low values of SOS ($7 \cdot 10^4$).

Table 2. Artificial neural network model summary (performance and errors) and the "goodness of fit" tests for the developed ANN model

Network	**Performance**			**Error**			**Train.**	**Error**	**Hidden**	**Output**
name	Train.	Test.	Valid.	Train.	Test.	Valid.	algor.	funct.	activ.	activ.
MLP 3-9-1	0.945	0.999	0. 999	$5 \cdot 10^4$	$2 \cdot 10^3$	$7 \cdot 10^5$	BFGS 32	SOS	Tanh	Identity

*Performance term represents the coefficients of determination, while error terms indicate the lack of data for the ANN model.

Optimal network, used for prediction of dispersion angles of spraying nozzle for glycerol and soybean oil was able to predict reasonably well the output for a broad range of the process variables. As it is shown in Figure1, the predicted values were very close to the experimental (target) values in most cases, in terms of r^2 value of the ANN model.

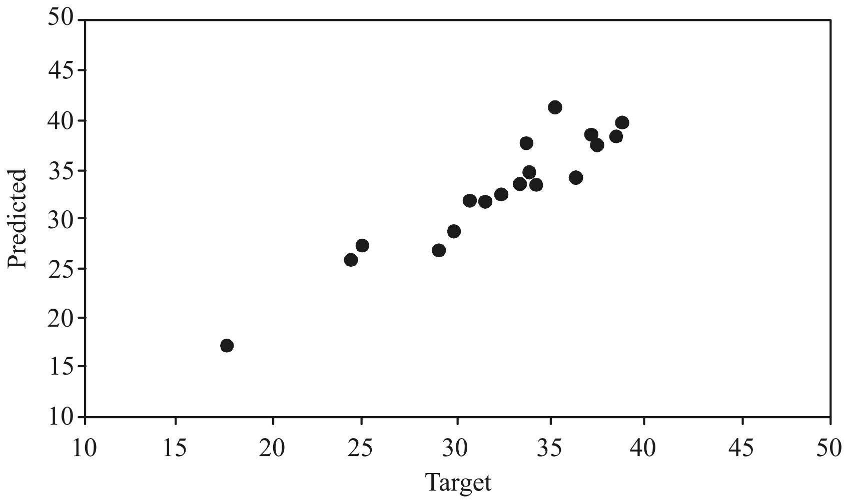

Figure 1. The comparison of experimentally obtained and calculated values of dispersion angles of spraying nozzle for glycerol and soybean oil

The quality of the model fit was tested and the residual analysis of the developed model was presented in Table 3. The ANN model had an insignificant lack of fit tests, which means the model satisfactorily predicted the dispersion angles of spraying nozzle for glycerol and soybean oil. A high r^2 is indicative that the variation was accounted for and that the data fitted the proposed model satisfactorily (28).

Table 3. The 'goodness of fit' tests of the developed mathematical models

	χ^2	RMSE	MBE	MPE	r^2	Skew.	Kurt.	Mean	StDev	Var
Angle	4.609	2.086	-0.727	4.548	0.945	-1.155	2.041	-0.727	2.012	4.049

r^2 - coefficient of determination, χ^2 - reduced chi-square, MBE - mean bias error, RMSE - root mean square error, MPE - mean percentage error, Skew. - skewness, Kurt. - kurtosis, StDev - standard deviation, Var - variance.

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The mean and the standard deviation of residuals have also been analysed. The mean of residuals for the ANN model was equal to -0.727, and the standard deviation was 2.012. The skewness parameter showed minimal deviations from a normal distribution, -1.155, while the kurtoisis parameter showed almost neglecting the difference in "peakedness" compared to normal distribution, 2.041. The coefficient of determination (0.945), the mean relative percent error (4.548), the root mean square error (2.086) and the reduced chi-square (4.609) were the evaluated values of developed ANN. According to these results, it was confirmed that obtained ANN model was statistically significant and in agreement with experimental results.

Table 4 presents the elements of matrix W_1 and vector B_1 (presented in the bias row), and Table 5 presents the elements of matrix W_2 and vector B_2 (bias) for the hidden layer, used for calculation in Equation 1.

Table 4. Elements of matrix W_1 and vector B_1 (presented in the bias row)

Neuron	1	2	3	4	5	6	7	8	9
Temp	0.58	-0.16	0.58	-2.00	-1.08	-0.17	0.92	-1.57	-2.08
Diameter	-0.20	-0.21	0.62	-0.57	0.24	-0.66	0.07	0.37	-1.08
Glycerol	-0.17	0.18	0.11	1.18	-0.19	0.45	-0.01	-0.42	-0.17
Soybean oil	0.27	-0.18	0.08	-0.90	0.20	0.23	0.17	0.04	0.65
Bias	0.22	-0.08	0.17	0.38	-0.14	0.76	0.14	-0.39	0.46

Table 5. Elements of matrix W_2 and vector B_2 (presented in the bias column)

Neuron	1	2	3	4	5	6	7	8	9	Bias
Angle	-0.68	0.32	-0.22	-0.88	0.70	1.70	-0.35	0.47	-1.01	0.30

CONCLUSIONS

An ANN-based model can be applied for various parameter analysis for spraying system by nozzle. In this study the ANN-based model was developed for prediction of dispersion angles of spraying nozzle for a wide range of input variables. The experimental results were obtained following the full factorial experimental design with two parameters (temperature and nozzle diameter), three levels, and two types of fluids (the total number of runs was: $3^2 \times 2 = 18$). The developed model could be effectively used for predictive purposes and optimization of liquids application in animal feed production. Taking into account that a wide variety of data were used in the present work to obtain the ANN model, and since the model turned out to yield a good representation of the experimental data, it can be very useful in practice. Considering the actuality of the topic, further broad researches are desirable in the field of application of liquids in animal feed production.

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