ESTIMATION OF NUTRIENT CONCENTRATIONS IN RUNOFF FROM BEEF CATTLE FEEDLOT USING ADAPTIVE NEURO-FUZZY INFERENCE SYSTEMS

H. Simsek[*], *B. Cemek*[†], *M.S. Odabas*[‡], *S. Rahman*[*]

Abstract: Nutrient concentrations in runoff from beef cattle feedlots were estimated using two different adaptive network-based fuzzy inference systems (ANFIS), which were: (1) grid partition (ANFIS-GP) and (2) subtractive clustering based fuzzy inference system (ANFIS-SC). The input parameters were pH and electrical conductivity (EC); and the output parameters were total Kjeldahl nitrogen (TKN), ammonium-N (NH_4-N), orthophosphate (ortho-P), and potassium (K). Models performances were evaluated based on root mean square error, mean absolute error, mean bias error, and determination coefficient statistics. For the same dataset, the ANFIS model outputs were also compared with a previously published nutrient concentration predictability model for runoff using artificial neural network (ANN) outputs. Results showed that both ANFIS-GP and ANFIS-SC models successfully predicted the runoff nutrient concentration. The comparison results revealed that the ANFIS-GP model performed slightly better than ANFIS-SC model in estimating TKN, NH_4-N, ortho-P, and K. When compared with the ANN model for the same dataset, ANFIS outperformed ANN in nutrient concentration prediction in runoff.

Key words: *nutrient concentration, cattle feedlot, grid partition based fuzzy inference system (ANFIS-GP), subtractive clustering based fuzzy inference system (ANFIS-SC)*

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1. Introduction

With expanding livestock facilities, animal agriculture is facing increasing environmental concerns, i.e., water and air pollution due to increased manure volume. Although manure is an excellent source of nutrients for plants and a good soil conditioner, improper manure management, especially from feedlots, can negatively

[*]Halis Simsek, Shafiqur Rahman – Corresponding author, Agricultural & Biosystems Engineering, North Dakota State University, Fargo, North Dakota, USA, E-mail: `s.rahman@ndsu.edu`

[†]Bilal Cemek, Department of Agricultural Structures and Irrigation, Faculty of Agriculture, Ondokuz Mayis University, Samsun, Turkey

[‡]Mehmet Serhat Odabas, Bafra Vocational School, Ondokuz Mayis University, Samsun, Turkey

influence water quality. Runoff from open animal feeding operations has long been known as a source of groundwater and surface water pollution. According to Koelsch [10], runoff from feedlots is a major contributor and will continue to be a contributor to surface and groundwater impairment.

Transport and accumulation of nutrients in downstream surface water can seriously affect the living organisms in the water body since the excess amount of nutrient loading promote algal growth, cause oxygen depletion and ultimately cause eutrophication in the water ecosystem [14, 16, 18]. Controlling runoff from feedlots, barnyards and other livestock facilities prevents the surface water contamination from runoff. Discrete sampling is good to get an idea of nutrient concentration, but it does not provide any diurnal trend. Continuous monitoring of nutrient concentrations overcome discrete sampling limitation, but in case of runoff sampling it is an expensive and time consuming process due to automation of a system and logistical supports needed to set up an automatic system. Therefore, there is a need to develop a model capable of predicting feedlot runoff quality with easily measurable parameters such as pH and EC.

There are many available techniques, such as multiple linear regressions (MLR) and artificial intelligence that can be used for prediction and classification purposes. MLR, which is a traditional statistical tool, is being widely used to learn about the relationship between several independent variables and a dependent variable. However, those well-established statistical tools are not suitable to address more complex and nonlinear problems. Artificial intelligence techniques, such as artificial neural network (ANN) and adaptive network-based fuzzy inference systems (ANFIS) can overcome these difficulties since these techniques have remarkable learning capabilities.

The artificial intelligence techniques are broadly used in the field of surface and groundwater hydrology and hydraulics to predict; sediment transport and accumulation, evaporation, evapotranspiration, rainfall, and surface and watershed runoff [3-7, 11, 13, 15, 17, 20]. Nevertheless, there is only one study available on the modeling of nutrient concentrations on animal feedlot runoff using ANN [13]. ANFIS has not been used previously to predict nutrient concentration from feedlot runoff, or compared its predictability with ANN or other models.

Kisi et al. [15] has performed a gene expression programing (GEP) technique, which is another intelligence technique, to estimate runoff from rainfall in a small catchment and they have found that GEP is capable of modeling the rainfall-runoff data successfully. Another intelligence technique, explicit neural network (ENN) has been used to estimate sediment volume carried by a river [3]. Results from that study showed that ENN performs better than MLR and nonlinear regression models on estimating sediment volume. In the study, ANFIS model predictability has been compared with ANN.

Fuzzy inference system (FIS) can describe the complex and non-linear phenomena with the precise rules [6, 11]. The fuzzy model, which relies on the fuzzy logic, was first created by Zadeh [20] as a mathematical tool to build a fuzzy logic of a system that works by applying neural learning rules to identify the structure of a FIS. It is a powerful design technique that serves as a basis to build a fuzzy "if-then" rules or fuzzy conditional statements as a form of "if A then B". In the statement, A and B represent the fuzzy set characterized by membership function

(MF). Takagi and Sugeno [17] conducted a systematic study on fuzzy modeling to identify the structure of the FIS and they improved the fuzzy implication by reducing the number of implication and simplifying the reasoning.

Following the previous studies on fuzzy logic, Jang [7] developed the architecture and learning procedure to transform human knowledge or experience into a fuzzy inference system and he called this technique as ANFIS. ANFIS uses ANN learning algorithms and fuzzy reasoning to employ fuzzy if-then rules. The model minimizes the sum of squared errors between the desired and the actual output by creating a fuzzy decision tree. There are two types of ANFIS, which are the grid partition based fuzzy inference system (ANFIS-GP) and subtractive clustering based fuzzy inference system (ANFIS-SC) [5]. In this study, ANFIS-GP and ANFIS-SC, were used to investigate the relationship between nutrient content, and physical and chemical properties of runoff samples from beef cattle feedlots. Also, these models output using the same dataset was compared with previously published nutrient concentration in runoff prediction capability using the ANN. In both cases, the model has two inputs and one output parameters. The input parameters were EC and pH and output parameters were TKN, NH_4-N, ortho-P, and K, where only one output parameter was used at a time.

2. Material and method

2.1 Study site

The study site is located at +46° 33' 45.46" N and -97° 8' 27.60" W in Fargo, ND, USA. The average annual rainfall in the study area is 468 mm. The soil type is sandy loam. The length and width of the pen were 76 and 62 m, respectively, and overall aggregate slope of the feedlot about 5% was achieved by incorporating mounds in the pen. Feedlot has sandy loam soil and classified as hydrologic soil group A. The feedlot was designed for 500 head of beef cattle with two pens, but only one pen was operational, and runoff was collected from that pen only. Feedlot manure was scrapped once in a year during fall. Additional information can be found in Rahman et al. [15].

2.2 Experimental procedure and description of data

About 380 runoff samples were collected using automatic samplers (ISCO 6712, Teledyne ISCO Inc., Lincoln, NE). ISCO samplers were powered by heavy duty marine batteries, which were charged by solar panel. Runoff in each sampling location was accumulated into a 60 liter bucket, and samples were collected from the bucket using ISCO samplers, which were activated via liquid level actuator (model: 1640, sampler actuator, Teledyne ISCO Inc., Lincoln, NE). Immediately after collection, samples were brought to laboratory for analyses. Standard methods of analysis were employed to analyze runoff samples for determining nutrients (ortho-P, TP, NH_4-N, NO_3-N, TKN, TN, and K), solids concentrations, pH, and electrical conductivity (EC). Electrical conductivity and pH were analyzed using a handheld meter (YSI Pro Plus, YSI Inc., Ohio, USA). Solids and nutrients were analyzed at

Soil Testing and Waste Management Laboratory of North Dakota State University. A detailed analysis procedure has been described in Rahman et al. [15].

2.3 Application of artificial intelligence techniques

Artificial intelligence techniques are suitable to solve high dimensional and nonlinear problems because of their ability to recognize and learn from input and output. In this study, two types of ANFIS, the grid partition based fuzzy inference system (ANFIS-GP) and subtractive clustering based fuzzy inference system (ANFIS-SC) were used to investigate the relationship between nutrient content, and physical and chemical properties of runoff samples from beef cattle feedlots. At the same time, runoff nutrient predictability using ANN in a previous study [4] has been compared with the current ANFIS method using the same dataset. These results were used to compare the predictability of two models.

Both ANN and ANFIS have learning process, additionally, ANFIS has sufficient number of fuzzy rules created from expert knowledge to describe the input and output relation of a problem. Overall, the selection of the tools to predict the output with a high accuracy depends on the type of problem to be solved [3, 13, 17]. Each ANFIS systems have been described below.

2.3.1 Adaptive neuro-fuzzy interference system (ANFIS)

ANFIS is a non-linear, data driven, self-adaptive approach, and it can identify and learn correlated patterns between input data sets and corresponding target values, even when the underlying data relationship is unknown [19]. ANFIS have many applications in many areas, such as function approximation, intelligent control, time series prediction and agricultural information [1, 2, 12]. In ANFIS, it has generated a large numbers of rules for the system, but not all the rules are being used. This is one of the advantages of ANFIS where it will extract the best rules from the system. The most significant advantage of using ANFIS is that all its parameters can be trained within the structure of a fuzzy logic system [9].

ANFIS-GP used in this study has three different membership functions (MFs) named as: triangular (tri), trapezoidal (trap), and Gaussian (Gauss). All MFs were performed for each training, testing, and validation purposes, but only training and testing results were presented. For the single input parameter, which was EC, 3 and 4 MFs were tested while, for two input parameters, which were EC and pH, 3×3 and 4×4 MFs were tested for each training, testing and validation data sets.

ANFIS-SC is important to determine the influential radius parameter for ANFIS-SC using trial-and-error approach. For the ANFIS-SC model, 3 and 4 MFs were tested for a single input parameter (EC) with three different radii (0.6, and 0.8 cm for MF-4, and 1.25 cm for MF 3). However, 4, 6, 4×4, and 5×5 MFs were tested for two input parameters (EC-pH) with three different radii (0.6 cm for MF 8×8, 0.8 cm for MF 6×6, and 1.25 cm for MF 4×4) for training, testing and validation data sets.

ANFIS algorithm was used to build a fuzzy model of a system to predict unknown data. Fig. 1 represents a typical architecture of two-input ANFIS model with fixed nodes (circles) and adaptive nodes (squares). The figure contains input nodes (layer 1), hidden layers (layers 2, 3, and 4), and an output node (layer 5).

The nodes in the hidden layers are functioning as MFs and rules. Layer 1 is referred to as premise parameters contain two MFs (fuzzy subspace) associated to each input parameter. Each subspace in layer 1 is partitioned to other subspaces in layer 2 and 3. Both layers 2 and 3 are governed by a fuzzy if-then rule. Finally, layer 4 is referred to as consequent parameters delineate the output with in fuzzy subspace [7]. The ANFIS architecture in Fig. 1 is the same as the architecture used in the model with either one or two input parameters (pH and EC) or the best prediction results were presented in this study.

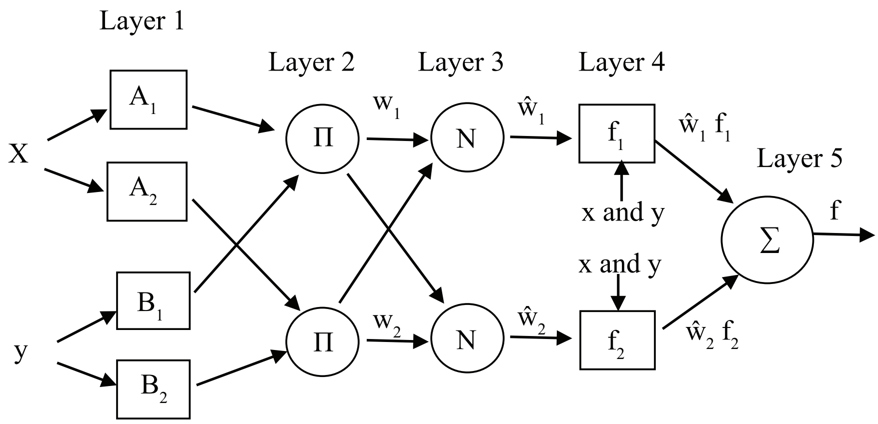

Fig. 1 *A typical architecture of an ANFIS [7].*

Jang [7] simplified a typical rule set with two fuzzy "if-then" rules as follows:

Rule 1: If x is A_1 and y is B_1, then $\mathrm{f}_1 = p_1x + q_1y + r_1$,

Rule 2: If x is A_2 and y is B_2, then $\mathrm{f}_2 = p_2x + q_2y + r_2$.

Here x and y are two input variables, the A and B denote the linguistic terms of the node function, and the r, p and q are referred to as consequent parameters. The details and mathematical background of ANFIS and the detailed description of each layer in Fig. 1 can be found in Jang and Jang et al. [7, 8].

Training, testing, and validation processes were performed for both ANFIS-GP and ANFIS-SC with only one input parameter (EC) or two input parameters (EC and pH) to estimate one output such as NH_4-N, TKN, ortho-P, or K at a time. Training processes were applied to minimize the mean square error (MSE) between the input parameter(s) and the desired output parameter of the system. Weights of the connections were adjusted in the neural network. In order to obtain sufficiently accurate and reliable results, the training data set must represent all the important characteristics of the entire data set. Based on this criterion, training data set was formed using independent variables on the data available. Before starting to run the model to predict the unknown data, the model was tested using the data set that was not used during the training process.

Testing process provides more reliable evaluation and comparison of the data. Root mean square error (RMSE), mean absolute error (MAE), mean bias error

(MBE) and coefficient of determination (R^2) statistics are used as comparing criteria for the evaluation of the models' performances. The statistical parameters, which are mean, standard error (SE), standard deviation (SD), minimum values (min), maximum values (max), and coefficient of variance (CV) were calculated for training and testing data sets for input and output parameters.

3. Results and discussion

In this study, NH_4-N, TKN, ortho-P, and K concentrations were estimated as output parameters using EC and pH inputs. The best estimation data set was determined by analyzing the statistical parameters for testing and training data sets. The statistical parameters, which were mean, SE, SD, CV, minimum and maximum values were presented in Tab. I for training and testing data sets. Tab. I showed that the minimum and maximum values of the training and testing data sets for both input (EC and pH) and output parameters (NH_4-N, TKN, ortho-P, and K) were comparable which explained that the data obtained in this study were sufficient to run the model. Similarly, other parameters such as mean, SE, SD, and CV values for either input or output parameters were observed and found very close each other in both training and testing data sets. These results proved that selected input and output data sets were acceptable to run the model.

3.1 Estimation of NH_4-N, TKN, ortho-P, and K

ANFIS-GP and ANFIS-SC models were applied for the single (EC) and two (EC-pH) input parameters to estimate NH_4-N, TKN, ortho-P, and K. Cemek et al., [4] conducted a study in the same sampling area to determine the relationship between input and output parameters. They found that output parameters (NH_4-N, TKN, ortho-P, and K) are affected when the input parameters (EC and pH) are varied. Modeling results from this study also proved that there is a strong relationship between input and output parameters. Additionally, Cemek et al. [4] applied MLR and ANN methods to predict NH_4-N, TKN, ortho-P, and K for the same dataset used in this study, and their results were compared with the ANFIS output.

For ANFIS-GP models with tri, trap, and Gauss MFs were tested for each input parameter. The number of MFs was 3 and 4 for EC parameter and 3×3 and 4×4 for EC-pH parameters. All the results for ANFIS-GP were presented in the Tabs. II, IV, VI, and VIII. For ANFIS-SC model, the number of MFs was 3 and 4 for EC parameter and 4×4, 5×5, 6×6, 8×8, 9×9, and 10×10 for EC-pH parameters. Additionally, radii for ANFIS-SC were 0.6, 0.8, and 1.25 cm for either EC or EC-pH inputs. All the results for ANFIS-SC were presented in the Tabs. III, V, VII, and IX. The best estimated results for both models were presented in the Tabs. II through IX and highlighted in gray color. Estimated versus measured data for the best estimated results were plotted and presented in the figures following each table.

About 70% data sets were used to train the model while the rest of the data sets were used for testing purposes to predict the outputs. RMSE and R^2 were crucial for determining ANFIS-SC model that were consisted of different number of fuzzy

		Parameter	Mean	SE	SD	Min	Max	CV
Training	input	pH	7.65	0.03	0.3	6.95	8.24	3.92
	input	EC	1591	79.4	895	329	3507	56.24
	output	NH_4-N	10.2	0.57	6.44	0.32	35.53	63.04
Testing	input	pH	7.6	0.05	0.31	6.77	8.05	4.12
	input	EC	1486	159	931	379	3441.5	62.6
	output	NH_4-N	10.59	1.35	7.89	0.4	31.78	74.4
Training	input	pH	7.67	0.03	0.32	7.03	8.24	4.17
	input	EC	1685	97.1	1027	329	3735	60.95
	output	TKN	74.0	4.06	42.95	1	161	58.06
Testing	input	pH	7.76	0.03	0.2	7.4	8.12	2.54
	input	EC	1837	170.8	981	379	3318	53.4
	output	TKN	76.4	8.25	47.37	8.6	147	62
Training	input	pH	7.7	0.02	0.31	6.95	8.24	4.03
	input	EC	1785	68.6	905	329.0	3636	50.71
	output	ortho-P	14.5	0.49	6.48	0.11	26.03	44.69
Testing	input	pH	7.65	0.04	0.31	6.81	8.13	4
	input	EC	1921	142.1	1044	379.5	3442	54.3
	output	ortho-P	14.21	1.07	7.83	0.11	24.47	55.1
Training	input	pH	7.7	0.02	0.3	6.95	8.21	3.90
	input	EC	1837	61.1	862	329	3736	46.92
	output	K	436	18.13	255	10.73	992	58.57
Testing	input	pH	7.66	0.04	0.28	6.77	8.18	3.64
	input	EC	2041	120.8	958	379.5	3423	46.96
	output	K	492	34	277	12.26	903	56.34

Tab. I *Statistical parameters for input (EC and pH) and output (NH_4-N, TKN, ortho-P and K) variables.*

rules. The different numbers of MFs were tested and the lowest RMSE values were selected. In a previous study, ANFIS-SC model has been used for estimating daily pan evaporation and different RMSE values were found for the different number of inputs [9]. RMSE values were 0.95, 0.77, 0.50, and 0.22 for one, two, three, and four inputs, respectively. Adding fourth input to the model increased ANFIS model's performance by reducing RMSE values to 56% [9]. In this study, the best estimated training results were selected from each tables and corresponding testing data set for the same MF also selected accordingly. The best estimated results are also shaded to gray color each table. The statistical parameters, which were R^2, MBE, MAE, and RMSE were calculated for each training and testing data set and presented in Tabs. II through V. RMSE and correlation played important roles in determining ANFIS model which were consisted of different number of fuzzy rules.

3.1.1 Estimation of NH_4-N

The effect of a single input parameter, EC, and two input parameters, EC-pH, on the NH_4-N was modeled using ANFIS-GP and ANFIS-SC models. Based on the multiple linear regression analysis conducted by Cemek et al. [4] for the same study site, NH_4-N concentrations were found highly correlated with EC and pH input parameters since the highest ammonium was observed at high EC and low pH values or lowest ammonium concentration was observed with high EC and high pH values. Statistical parameters were analyzed and the best NH_4-N prediction data was selected for both ANFIS-GP and ANFIS-SC models and results were presented in Tabs. II and III, respectively.

	Name	Input	No. of MF	Input MF	R^2	MBE	MAE	RMSE
Training data set				Tri	0.87	−0.02	1.78	2.29
	ANFIS-GP	EC	3	Trap	0.89	0.02	1.74	2.14
				Gauss	0.85	−0.24	1.93	2.46
				Tri	0.89	−0.39	1.53	2.20
	ANFIS-GP	EC	4	Trap	0.86	−0.28	1.75	2.44
				Gauss	0.87	0.33	1.70	2.32
				Tri	0.87	0.00	1.82	2.33
	ANFIS-GP	EC-pH	3×3	Trap	0.95	0.00	1.11	1.47
				Gauss	0.96	0.01	1.02	1.35
				Tri	0.97	0.00	0.84	1.15
	ANFIS-GP	EC-pH	4×4	Trap	0.97	0.00	0.80	1.09
				Gauss	**0.97**	**0.00**	**0.77**	**1.08**
Testing data set				Tri	0.92	0.10	1.59	1.98
	ANFIS-GP	EC	3	Trap	0.93	0.44	1.54	1.98
				Gauss	0.93	0.17	1.53	1.91
				Tri	0.93	0.16	1.44	1.90
	ANFIS-GP	EC	4	Trap	0.96	0.75	1.08	1.66
				Gauss	0.97	0.42	1.01	1.34
				Tri	0.89	0.26	1.75	2.35
	ANFIS-GP	EC-pH	3×3	Trap	0.91	−0.21	1.72	2.17
				Gauss	0.91	−0.35	1.64	2.12
				Tri	0.93	−0.28	1.44	1.81
	ANFIS-GP	EC-pH	4×4	Trap	0.92	−0.42	1.39	2.10
				Gauss	**0.94**	**0.24**	**1.14**	**1.76**

Tab. II *Estimating NH_4-N for the inputs of EC and pH data using ANFIS-GP model.*

For ANFIS-GP model, the best estimated NH_4-N values were selected for the EC-pH input parameters for 3×3 and 4×4 MF and tri, trap, and Gauss methods. All the EC-pH inputs produced suitable results since R^2 values are varied between 0.87 and 0.97 and RMSE values are varied between 1.08 and 2.33. Testing for EC-pH inputs are also acceptable since R^2 s are higher and RMSEs are lower.

Gauss method for 4×4 MF with the highest R^2 values (0.97), the lowest RMSE values (1.08), and the lowest MBE and MAE values for training data sets and corresponding testing data sets for this training data with high R^2 value (0.94), the low RMSE value (1.76), and the low MBE and MAE values were presented in Fig. 2.

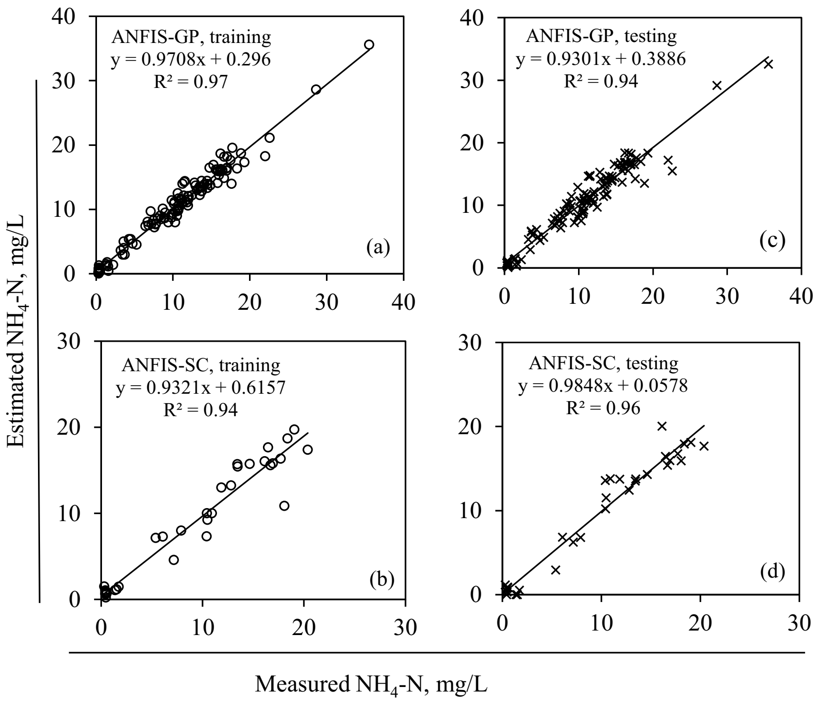

Fig. 2 *The measured and estimated NH_4-N concentrations [mg/L] for the inputs of EC-pH using ANFIS-GP and ANFIS-SC models.*

Single input (EC) modeling results are also acceptable to estimate ammonium since R^2 s are higher than 0.85 for training and higher than 0.92 for testing data sets. This result explained that ammonium can be estimated using only EC input if pH is not available.

The relationships between inputs and outputs were 97% for training and 94% for testing data sets explained that the ANFIS-GP model produced high accuracy for two input parameters (EC-pH) compare to single input (EC) parameter. This outcome explained that the model can predict NH_4-N with 3% error for training and 6% error for testing data sets for EC-pH (Fig. 2a, c). Cemek et al. [4] found slightly lower correlation (R^2 value was 0.92 and 0.85 for ANN and MLR, respectively) to estimate NH_4-N in runoff sample.

For ANFIS-SC model, the estimated NH_4-N values were modeled for the EC and EC-pH input parameters with 3, 4, 4×4, 6×6, 8×8 MF and 0.6, 0.8, and 1.25 cm radii. All the EC-pH inputs produced suitable results since R^2 values are varied between 0.91 and 0.94 and RMSE values are varied between 1.56 and 1.94 for training data sets. Testing data for these training data are also produced high R^2 (varied between 0.92 and 0.96) and low RMSE (varied between 1.45 and

	Name	Input	Radii	No. of MF	R^2	MBE	MAE	RMSE
Training data set	ANFIS-SC	EC	0.6	4	0.87	−0.35	1.75	2.3
			0.8	4	0.89	−0.31	1.55	2.13
			1.25	3	0.83	−0.35	2.10	2.66
	ANFIS-SC	EC-pH	0.6	8×8	0.94	0.07	1.09	1.56
			0.8	6×6	0.92	0.00	1.35	1.78
			1.25	**4×4**	**0.91**	**0.00**	**1.47**	**1.94**
Testing data set	ANFIS-SC	EC	0.6	4	0.97	0.52	1.08	1.41
			0.8	4	0.97	0.55	0.99	1.4
			1.25	3	0.95	0.20	1.23	1.6
	ANFIS-SC	EC-pH	0.6	8×8	0.92	0.12	1.43	1.97
			0.8	6×6	0.92	−0.14	1.41	1.94
			1.25	**4×4**	**0.96**	**0.08**	**1.07**	**1.45**

Tab. III *Estimating NH_4-N for the inputs of EC and pH data using ANFIS-SC model.*

1.97) values. The best estimated NH_4-N value was selected for the EC-pH input parameters with radii of 1.25 and MF of 4×4 for both training and testing data sets and the measured and estimated NH_4-N concentrations [mg/L] were presented in Fig. 2a and c, which are; (a): 4×4 MF using Gauss method for training data sets, (c): 4×4 MF using Gauss method for testing data sets.

Tab. III shows that single input parameter EC may also be used to predict ammonium in runoff with high R^2 (≥ 0.87) and low RMSE (≤ 2.66) values for both training and testing data. Overall, the results explain that either EC or EC-pH inputs can be used to predict ammonium accurately.

For ANFIS-SC, the relationships between inputs and outputs were 91% for training and 96% for testing data sets expressed that the model predicted NH_4-N with 9% and 4% errors for training and testing, respectively, for two input parameters (EC-pH) compare to single input (EC) parameter in Fig. 2b and d, which are; (b): 1.25 cm radius and 4×4 MF for training data sets, (d): 1.25 cm radius and 4×4 MF for testing data sets.

3.1.2 Estimation of TKN

EC and EC-pH inputs were analyzed for the estimated TKN parameters and results showed that EC-pH inputs produced the best outcome compare to single parameter (EC) for both ANFIS-GP and ANFIS-SC models (Tab. IV). Tri, trap, and Gauss methods; 3, 4, 3×3, 4×4, and 10×10 MFs; and 0.6, 0.8, and 1.25 cm radii were used for both models. Trap method with 4×4 MFs was selected for the best ANFIS-GP model for EC-pH inputs (Figs. 3a and c). In Fig. 3, (a) is 4×4 MF with Gauss method for training data sets; (c) is 4×4 MF with Gauss method for testing data sets. The highest R^2 is 0.98 and the lowest RMSE is 6.17 and MBE and MAE values were lowest for training and testing data sets (Tab. IV).

The ANFIS-GP model results explained that single input parameter EC produced a good estimation data to predict TKN with high R^2 (high as much as 0.98)

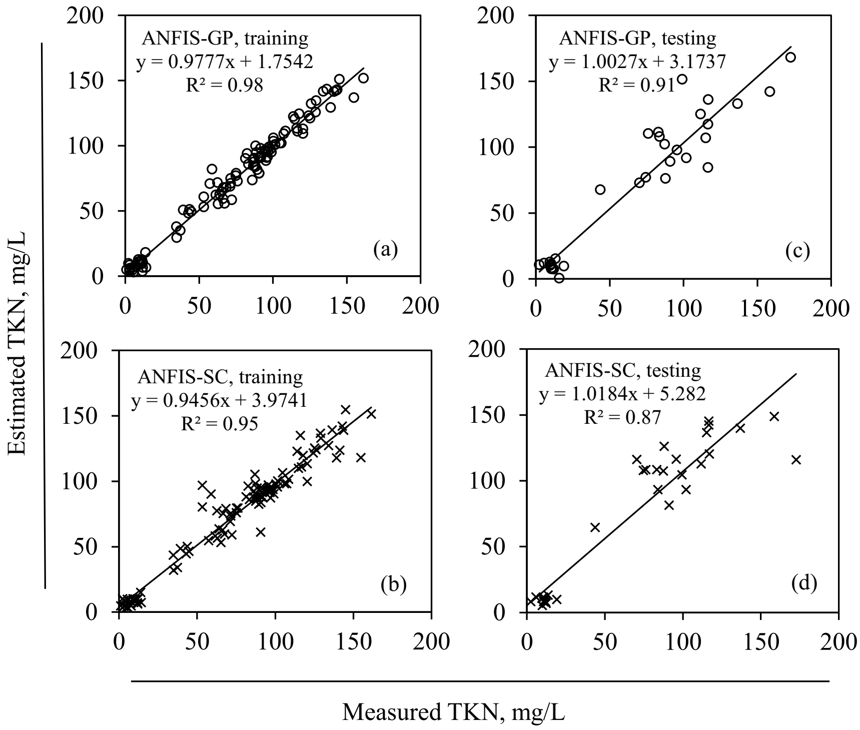

Fig. 3 *The measured and estimated TKN values [mg/L] for the inputs of EC and pH using ANFIS-GP and ANFIS-SC model.*

and low RMSE (low as much as 6.17) values for both training and testing data. Overall, the results explain that either EC or EC-pH inputs can predict TKN with a high accuracy.

For ANFIS-SC model of TKN, the best radius for EC-pH inputs was 0.6 cm with 10×10 MF and the highest R^2 (0.95) and the lowest RMSE (9.82) for training and values. R^2 value for the ANFIS-SC was 0.84 and RMSE was 22.88 for the corresponding testing data sets with 0.6 cm radius and 10×10 MF (Tab. V, Figs. 3b and d). In Fig. 3, b is 0.6 cm radius and 10×10 MF for training data sets; (d) is 0.6 cm radius and 10×10 MF for testing data sets. For EC, R^2s are higher than 0.75 and RMSEs are lower than 23.79, which indicate that single input parameter can be used to predict TKN (Tab. V). Overall, these results explained that ANFIS-GP model produced slightly better prediction for both single and two inputs than ANFIS-SC model for TKN estimation. For the same dataset, the TKN concentration predictability using the MLR model was R^2 = 0.88, RMSE = 20.45 and for the ANN model the predictability was R^2 = 0.88, RMSE = 17.03 [4]. Whereas, the ANFIS model improved the TKN predictability R^2 = 0.98, RMSE = 6.17). Therefore, both models may be used for predicting nutrient in runoff, but ANFIS model might improve predictability in some cases.

	Name	Input	No. of MF	Input MF	R^2	MBE	MAE	RMSE
Training data set	ANFIS-GP	EC	3	Tri	0.69	0	18.59	23.68
				Trap	0.60	0	23.42	27.13
				Gauss	0.66	0	20.4	24.96
	ANFIS-GP	EC	4	Tri	0.79	0	14.28	19.80
				Trap	0.78	0	13.48	20.06
				Gauss	0.78	0	13.75	19.97
	ANFIS-GP	EC-pH	3×3	Tri	0.93	−0.01	7.32	11.06
				Trap	0.95	−0.19	6.6	9.25
				Gauss	0.97	0	5.68	7.89
	ANFIS-GP	EC-pH	4×4	Tri	0.96	0	5.77	8.25
				Trap	0.97	0	5.4	7.91
				Gauss	**0.98**	**−0.1**	**4.56**	**6.17**
Testing data set	ANFIS-GP	EC	3	Tri	0.74	−5.46	19.13	26.12
				Trap	0.80	−8.63	20.97	25.44
				Gauss	0.75	−6.41	19.99	26.12
	ANFIS-GP	EC	4	Tri	0.84	−2.03	14.07	20.21
				Trap	0.84	−1.59	13.85	20.1
				Gauss	0.86	−1.98	13.5	18.91
	ANFIS-GP	EC-pH	3×3	Tri	0.91	−8.53	13.46	17.99
				Trap	0.87	−9.7	15.04	21.81
				Gauss	0.85	−13.42	18.36	27.21
	ANFIS-GP	EC-pH	4×4	Tri	0.69	−13.02	22.05	34.19
				Trap	0.77	−9.74	19.79	28.84
				Gauss	**0.91**	**−3.25**	**10.81**	**16.07**

Tab. IV *Estimating TKN for the inputs of EC and pH data using ANFIS-GP model.*

3.1.3 Estimation of ortho-P

The effect of single (EC) and two (EC-pH) input parameters on the estimation of ortho-P was examined using the ANFIS-GP and the ANFIS-SC models. A previous study showed that EC and pH inputs were highly correlated on the estimation of ortho-P and there was a curvilinear relationship between EC, pH and ortho-P. It was found that the ortho-P concentration increased when EC value was high and pH was low [4].

Tri, trap, and Gauss methods with 3, 4, 3×3, and 4×4 MFs for ANFIS-GP model were used to estimate ortho-P. Statistical results showed that the accuracy on the estimation of ortho-P was acceptable in both single and two input parameters. In ANFIS-GP model for ortho-P, R^2 values of EC inputs were lower compare to EC-pH inputs for training data, even though higher for testing data (Tab. VI). The highest R^2 values were 0.88 for training and 0.91 for testing, the lowest RMSE values were observed 2.22 for training and 2.66 for testing. One of the suitable results, which were 3×3 MF with trap method was selected to present in Fig. 4. In the Fig. 4; (a): EC-pH inputs for 3×3 MF using trap method for training

	Name	Input	Radii	No. of MF	R^2	MBE	MAE	RMSE
Training data set	ANFIS-SC	EC	0.6	9	0.83	0.01	12.00	17.71
			0.8	6	0.83	0.77	12.81	17.59
			1.25	3	0.75	0.00	15.24	21.48
	ANFIS-SC	EC-pH	**0.6**	**10×10**	**0.95**	**0.05**	**6.31**	**9.82**
			0.8	6×6	0.93	−0.01	7.51	11.45
			1.25	4×4	0.91	0.00	8.67	12.51
Testing data set	ANFIS-SC	EC	0.6	9	0.85	2.20	11.72	19.21
			0.8	6	0.86	3.04	12.68	19.19
			1.25	3	0.77	−1.61	16.81	23.79
	ANFIS-SC	EC-pH	**0.6**	**10×10**	**0.84**	**−8.19**	**15.89**	**22.88**
			0.8	6×6	0.84	−7.24	15.75	22.60
			1.25	4×4	0.87	−6.31	14.34	20.34

Tab. V *Estimating TKN for the inputs of EC and pH data using ANFIS-SC model.*

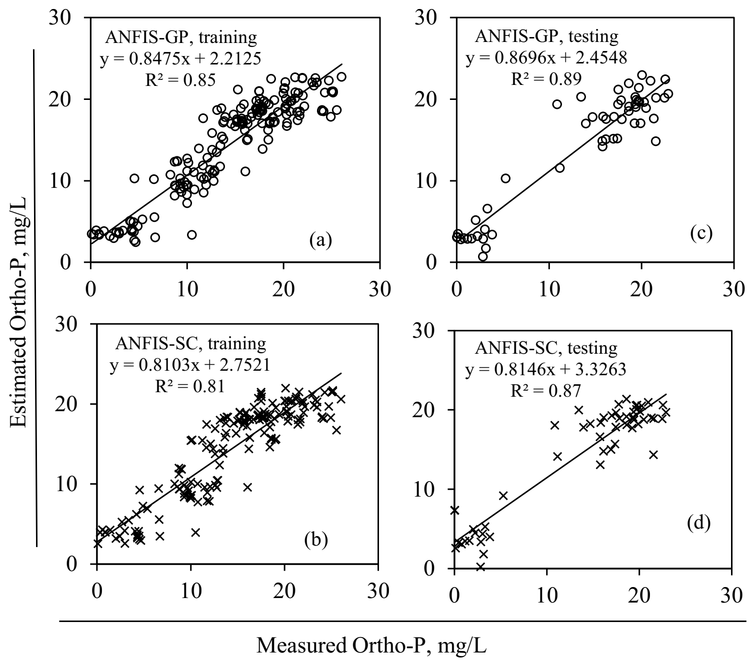

Fig. 4 *The measured and estimated ortho-P concentrations [mg/L] for the inputs of EC-pH using ANFIS-GP and ANFIS-SC models.*

data sets, (c): EC-pH inputs for 3×3 MF using trap method for testing data sets. For the same dataset, Cemek et al. [4] found a lower correlation coefficient for estimating ortho-P using the MLR (R^2 = 0.76; RMSE = 1.50) and ANN ($R^2 = 0.90$; RMSE = 0.69) model.

For ANFIS-SC model for ortho-P; 0.6, 0.8, and 1.25 cm radius with 3, 4, 6, 5×5, 9×9, and 10×10 MFs were used to estimate ortho-P. Similarly, for ANFIS-SC model, the highest R^2 values were observed as 0.85 for training and 0.91 for testing, the lowest RMSE values were observed as 2.48 for training and 2.72 for testing (Tab. VII). Both single and two input parameters were acceptable on the estimation of ortho-P. As an example, one of the models output for both training and testing data were presented in Fig. 4. In the Fig. 4; (b): EC-pH inputs for 1.25 cm radius and 5×5 MF for training data sets, (d): EC-pH inputs for 1.25 cm radius and 5×5 MF for testing data sets.

3.1.4 Estimation of K

The best K prediction data was analyzed for both single (EC) and two (EC-pH) input parameters for both ANFIS-GP and ANFIS-SC models (Tab. VIII). Model results were analyzed and both single and two input parameters were found as high

	Name	Input	No. of MF	Input MF	R^2	MBE	MAE	RMSE
Training data set	ANFIS-GP	EC	3	Tri	0.78	0	2.48	3
				Trap	0.76	0	2.62	3.16
				Gauss	0.77	0	2.57	3.08
	ANFIS-GP	EC	4	Tri	0.78	0	2.51	3.01
				Trap	0.78	0	2.5	3.01
				Gauss	0.78	0	2.53	3.04
	ANFIS-GP	EC-pH	3×3	Tri	0.85	0	2.02	2.51
				Tramp	**0.85**	**0**	**2.02**	**2.52**
				Gauss	0.87	0	1.8	2.36
	ANFIS-GP	EC-pH	4×4	Tri	0.87	0	1.76	2.35
				Trap	0.87	0	1.76	2.31
				Gauss	0.88	0	1.68	2.22
Testing data set	ANFIS-GP	EC	3	Tri	0.90	−0.99	2.31	2.86
				Trap	0.88	−0.87	2.42	3.03
				Gauss	0.90	−0.92	2.31	2.88
	ANFIS-GP	EC	4	Tri	0.91	−0.97	2.34	2.83
				Trap	0.90	−0.84	2.28	2.86
				Gauss	0.90	−0.98	2.35	2.89
	ANFIS-GP	EC-pH	3×3	Tri	0.83	−0.95	2.45	3.35
				Tramp	**0.89**	**−0.69**	**2.02**	**2.66**
				Gauss	0.70	−0.22	3.16	4.25
	ANFIS-GP	EC-pH	4×4	Tri	0.83	−1.41	2.58	3.49
				Trap	0.86	−0.5	2.24	2.92
				Gauss	0.65	−1.58	3.35	5.3

Tab. VI *Estimating ortho-P for the inputs of EC and pH data using ANFIS-GP model.*

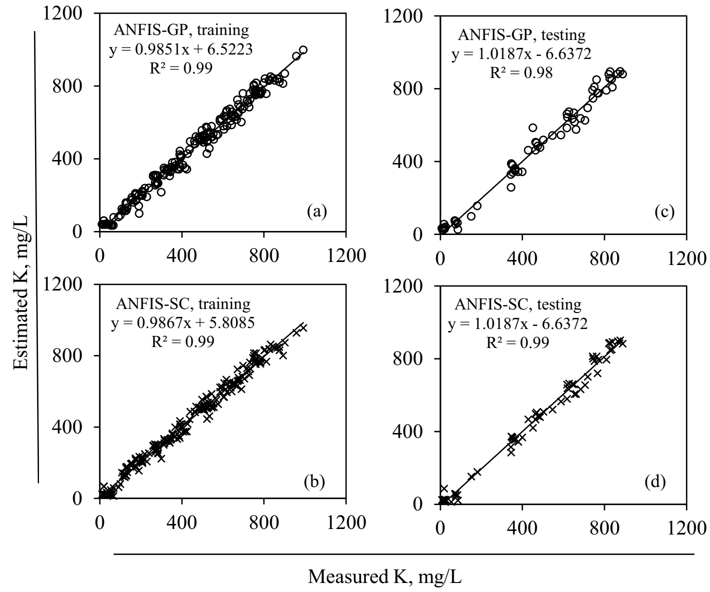

Fig. 5 *The observed and estimated K values for the inputs of EC and pH using ANFIS-GP and ANFIS-SC models.*

	Name	Input	Radii	No. of MF	R^2	MBE	MAE	RMSE
Training data set	ANFIS-SC	EC	0.6	6	0.79	0	2.49	2.99
			0.8	4	0.78	0	2.53	3.04
			1.25	3	0.72	−0.27	2.61	3.45
	ANFIS-SC	EC-pH	0.6	10×10	0.85	0	1.95	2.48
			0.8	9×9	0.85	0	1.95	2.48
			1.25	**5×5**	**0.81**	**0**	**2.32**	**2.81**
Testing data set	ANFIS-SC	EC	0.6	6	0.91	−0.82	2.22	2.72
			0.8	4	0.9	−0.96	2.32	2.86
			1.25	3	0.9	−1.02	2.38	2.94
	ANFIS-SC	EC-pH	0.6	10×10	0.83	−1.06	2.44	3.42
			0.8	9×9	0.83	−0.85	2.42	3.3
			1.25	**5×5**	**0.87**	**−0.82**	**2.26**	**2.92**

Tab. VII *Estimating ortho-P for the inputs of EC and pH data using ANFIS-SC model.*

accuracy on estimation of K for both models. As an example, 4×4 MF and Gauss method for both training and testing data sets were selected for EC-pH inputs and presented in Fig. 5. All three methods were produced the high

R^2 values (varied between 0.97–0.99 for training and 0.97–0.98 for testing) and the lowest RMSE values (22.78 for training and 40.28 for testing). In the Fig. 5; (a): EC-pH inputs for 4×4 MF using Gauss method for training data sets, (c): EC-pH inputs for 4×4 MF using Gauss method for testing data sets.

	Name	Input	No. of MF	Input MF	R^2	MBE	MAE	RMSE
Training data set	ANFIS-GP	EC	3	Tri	0.98	−0.09	8.35	31.9
				Trap	0.98	−0.19	8.1	31.55
				Gauss	0.98	−0.03	7.93	31.64
	ANFIS-GP	EC	4	Tri	0.98	0.14	7.82	37.69
				Trap	0.98	0.2	7.81	31.33
				Gauss	0.99	0.16	7.83	31.09
	ANFIS-GP	EC-pH	3×3	Tri	0.98	−8.34	32.79	42.33
				Trap	0.98	−3.41	29.01	36.26
				Gauss	0.98	−8.14	34.52	45.75
	ANFIS-GP	EC-pH	4×4	Tri	0.99	0.17	4.32	23.14
				Trap	0.99	0.25	5.53	23.55
				Gauss	**0.97**	**0.06**	**4.36**	**22.78**
Testing data set	ANFIS-GP	EC	3	Tri	0.98	−8.34	32.79	42.33
				Trap	0.98	−3.41	29.01	36.26
				Gauss	0.98	−8.14	34.52	45.75
	ANFIS-GP	EC	4	Tri	0.97	−9.62	38.69	52.72
				Trap	0.97	−9.76	35.89	50.95
				Gauss	0.98	−1.96	30.92	40.28
	ANFIS-GP	EC-pH	3×3	Tri	0.98	−8.34	32.79	42.33
				Trap	0.98	−3.41	29.01	36.26
				Gauss	0.98	−8.14	34.52	45.75
	ANFIS-GP	EC-pH	4×4	Tri	0.97	−9.62	38.69	52.72
				Trap	0.97	−9.76	35.89	50.95
				Gauss	**0.98**	**−1.96**	**30.92**	**40.28**

Tab. VIII *Estimating K for the inputs of EC and pH data using ANFIS-GP model.*

	Name	Input	Radii	No. of MF	R^2	MBE	MAE	RMSE
Training data set	ANFIS-SC	EC	0.6	4	0.99	0.2	7.82	30.98
			0.8	4	0.99	0.14	7.82	30.99
			1.25	3	0.98	−0.10	8.02	31.79
	ANFIS-SC	EC-pH	0.6	9×9	0.99	1.01	6.10	25.61
			0.8	6×6	0.99	0.80	6.26	25.86
			1.25	**4×4**	**0.99**	**0.99**	**7.45**	**29.34**
Testing data set	ANFIS-SC	EC	0.6	4	0.99	−7.06	27.66	33.80
			0.8	4	0.99	−7.30	27.75	33.86
			1.25	3	0.99	−8.93	30.07	36.28
	ANFIS-SC	EC-pH	0.6	9×9	0.99	−3.34	28.84	34.96
			0.8	6×6	0.99	−4.58	29.11	35.29
			1.25	**4×4**	**0.97**	**−2.02**	**27.05**	**33.56**

Tab. IX *Estimating K for the inputs of EC and pH data using ANFIS-SC model.*

For ANFIS-SC model, both single and two input parameters produced highly accurate estimation to predict K. Tab. IX showed that R^2 values were extremely high for both training and testing data sets. One example outcome for training and testing data has presented in Fig. 5. In the Fig. 5; (b): EC-pH inputs for 1.25 cm radius and 4×4 MF for training data sets, (d): EC-pH inputs for 1.25 cm radius and 4×4 MF for testing data sets. Comparing ANFIS-GP and ANFIS-SC, both models were acceptable to estimate K. A Comparison between ANFIS (this study) and ANN [4] showed that ANFIS provided higher predictability for the K concentration.

Overall, two types of fuzzy models, ANFIS-GP and ANFIS-SC were used in the current study for the data collected from a particular beef cattle feedlot. The same models are applicable to other beef cattle feedlots to estimate NH_4-N, TKN, ortho-P, and K using the pH and/or EC inputs parameters. However, for different types of animal feedlots, this model need to be calibrated based on feedlot nutrient characteristics, since runoff and manure nutrient characteristics may vary significantly based on animal diets and animal types.

4. Conclusions

The performance of adaptive fuzzy inference system was evaluated to estimate nutrient concentrations in runoff from beef cattle feedlot. Two fuzzy inference system models, which were ANFIS-GP and ANFIS-SC were used to estimate NH_4-N, TKN, ortho-P, and K using either single (EC) or two (EC-pH) input parameters. Results showed that all the output parameters were well modeled using fuzzy control rules. In general, GBP-FIS model performed slightly better than the ANFIS-SC model to estimate output parameters using either EC or EC-pH as inputs. Statistical results showed that both single and two input parameters were acceptable to estimate NH_3, TKN, ortho-P, and K for both ANFIS-GP and ANFIS-SC models. Two input parameters (EC-pH) provided higher accuracy to estimate all four output parameters compare to a single input parameter. Particularly, estimation of TKN performed better two input parameters. Nevertheless, in case of lack of pH, only EC value can be also used to predict all four output parameters with good predictability. In this study, ANFIS outperformed ANN in nutrient concentration prediction in runoff. GBP-FIS models may be used as means to estimate nutrient concentration easily and quickly when limited information is available.

References

[1] AL-HMOUZ A., SHEN J., AL-HMOUZ R., YAN J. Modeling and Simulation of an Adaptive Neuro-Fuzzy Inference System (ANFIS) for Mobile Learning. *IEEE T. Learn. Technol.* 2012, 5(3), pp. 226–237, doi: 10.1109/TLT.2011.36.

[2] AMIRYOUSEFI M.R., MOHEBBI M., KHODAIYAN F., ASADI S. An empowered adaptive neuro-fuzzy inference system using self-organizing map clustering to predict mass transfer kinetics in deep-fat frying of ostrich meat plates. *Comput. Electron. Agr.* 2012, 76(1), pp. 89–95, doi: 10.1016/j.compag.2011.01.008.

[3] BASHEER I.A. Selection of methodology for modeling hysteresis behavior of soils using neural networks. *J. Comput.-aided Civil Infrastruct. Eng.* 2000, 5(6), pp. 445–463.

[4] CEMEK B., RAHMAN S., RAHMAN A. Artificial neural network for predicting nutrients concentration in runoff from beef cattle feedlot. *Environmental Engineering and Management Journal*. 2013, 12(12), 2385–2396.

[5] COBANER M. Evapotranspiration estimation by two different neuro-fuzzy inference systems. *J Hydro.* 2011, 398(3-4), pp. 292–302, doi: 10.1016/j.jhydrol.2010.12.030.

[6] GANZLE M.G., KILIMANN K.V., HARTMANN C., VOGEL R., DELGADO A. Data mining and fuzzy modelling of high pressure inactivation pathways of Lactococcus lactis. *Innov. Food Sci. Emerg. Technol.* 2007, 8(4), pp. 461–468, doi: 10.1016/j.ifset.2007.04.003.

[7] JANG J.S.R. ANFIS - adaptive-network-based fuzzy inference system. *IEEE Trans. Syst. Man Cyb.* 1993, 23(3), pp. 665–685, doi: 10.1109/21.256541.

[8] JANG J.S.R., SUN C.T., MIZUTANI E. Neuro-Fuzzy and Soft Computing: A Computational Approach to Learning and Machine Intelligence. *Fuzzy rules and fuzzy reasoning.* 1st ed. Upper Saddle River, NJ: Prentice Hall, 1997, pp. 5–15.

[9] KODOGIANNIS V.S., LOLIS A. Forecasting Financial Time Series Using Neural Network and Fuzzy Systembased Techniques. *Neural Comput. Appl.* 2002, 11(6), pp. 90–102, doi: 10.1016/j.measurement.2012.03.025.

[10] KOELSCH R.K., LORIMERR K.R., MANKIN J.C. Vegetative treatment systems for management of open lot runoff: review of literature. *Applied Eng. in Agric.* 2006, 22(1), pp. 141–153.

[11] LERTWORASIRIKUL S. Drying kinetics of semi-finished cassava crackers: a comparative study. *LWT Food Sci. Technol.* 2008, 41(8), pp. 1360–1371, doi: 10.1016/j.lwt.2007.09.009.

[12] NADERLOO L., ALIMARDANI R., OMID M., SARMADIAN F., JAVADIKIA P., TORABI M.Y., ALIMARDANI F. Application of ANFIS to predict crop yield based on different energy inputs. *Measurement.* 2012, 45(1), pp. 1406–1413, doi: 10.1016/j.compag.2011.01.008.

[13] PALIWAL M., KUMAR U.A. Neural networks and statistical techniques: A review of applications. *Expert systems with applications.* 2009, 36(1), pp. 2–17, doi: 10.1016/j.eswa.2007.10.005.

[14] PEHLIVANOGLU E., SEDLAK D.L. Bioavailability of wastewater-derived organic nitrogen to the alga Selenastrum capricornutum. *Water Res.* 2004, 38(14–15), pp. 3189–3197, doi: 10.1016/j.watres.2004.04.027.

[15] RAHMAN A., RAHMAN S., BORHAN M.S. Performance evaluation of three vegetative filter strip designs for controlling feedlot runoff pollution. *Journal of Civil and Environmental Engineering.* 2013, 124(3), doi: 10.4172/2165-784X.1000124.

[16] SEITZINGER S.P., SANDERS R.W. Contribution of dissolved organic nitrogen from rivers to estuarine eutrophication. *Mar. Ecol. Prog. Ser.* 1997, 159, pp. 1–12, doi: 10.3354/meps159001.

[17] TAKAGI T., SUGENO M. Fuzzy identification of systems and its application to modeling and control. *IEEE Trans. Syst. Man Cyb.* 1985, 15(1), pp. 116–132, doi: 10.1109/TSMC.1985.6313399.

[18] URGUN-DEMIRTAS M., SATTAYATEWA C., PAGILLA K.R. Bioavailability of dissolved organic nitrogen in treated effluents. *Water Environ. Res.* 2008, 80(5), pp. 397–406, doi: 10.2175/106143007X221454.

[19] XING-MEI S., YING-TAO J., MEI Y., SHAO-KUN L., KE-RUM W., CHONG-TAO W. Artificial Neural Network to Predict Leaf Population Chlorophyll Content from Cotton Plant Images. *Agric. Sci. in China.* 2010, 9(1), pp. 38–45, doi: 10.1016/S1671-2927(09)60065-1.

[20] ZADEH L.A. Fuzzy sets. *Information and Control.* 1965, 8(3), pp. 338–353, doi: 10.1016/S0019-9958(65)90241-X.