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ARTIFICIAL NEURAL NETWORK BASED EQUATION TO ESTIMATE HEAD LOSS ALONG DRIP IRRIGATION LATERALS

Acácio Perboni[1], José Antonio Frizzone[2], Antonio Pires de Camargo[3]

ABSTRACT

This work proposes an equation based on Artificial Neural Network (ANN) to estimate head loss along emitting pipes accounting for cylindrical in-line emitters. The following input variables were used to fit the model: total head loss between two consecutive emitters; emitter spacing; internal diameter of the pipe; mean water velocity at uniform pipe sections; and, kinematic viscosity of water. The input data was obtained by experimental means and standardized from 0 to 1. Five replications and six distinct structures of ANNs multilayer perceptron (MLP) were used during the training stage performed using the package neuralnet of the software R. A MLP structure consisting of six neurons at input layer, six neurons at hidden layer, and one neuron at output layer was applied for fitting the model. Estimated values by the ANN's equation were compared to the estimated values by an equation based on dimensional analysis. The ANN's equation and the equation based on dimensional analysis presented maximum deviations between measured and estimated values of 0.324 kPa and 1.647 kPa, respectively. Therefore the ANN's equation presented better results than the equation based on dimensional analysis.

Keywords: microirrigation, model, fitting

EQUAÇÃO UTILIZANDO REDES NEURAIS ARTIFICIAIS PARA ESTIMAR PERDA DE CARGA EM TUBOS GOTEJADORES

RESUMO

[1] Eng° Agrônomo, Mestre, Doutorando ESALQ/USP, Piracicaba – São Paulo. Email: acacio_perboni@yahoo.com.br
[2] Eng° Agrônomo, Doutor, Professor Titular ESALQ/USP, Piracicaba – São Paulo. Email:frizzone@usp.br
[3] Eng° Agrônomo, Doutor, Especialista em Laboratório, INCTEI/ESALQ, Piracicaba – São Paulo. Email:apcpires@usp.br

Propor uma equação ajustada com rede neural artificial (ANN) para estimar a perda de carga em tubos emissores com emissores “in-line” do tipo cilíndrico, motivou a realização do presente estudo. As variáveis de entrada do modelo: perda de carga que ocorre entre dois emissores consecutivos; espaçamento entre emissores; diâmetro interno do tubo; área média da seção transversal de escoamento do emissor; velocidade média de escoamento da água no tubo e viscosidade cinemática da água foram obtidas experimentalmente e normalizadas no intervalo de 0 a 1. Cinco repetições para cada uma das seis diferentes estruturas de ANNs do tipo perceptron de múltiplas camadas (MLP) foram treinadas no pacote neuralnet do software R. A estrutura MLP com seis neurônios na camada de entrada, seis na oculta e um na camada de saída foi escolhida para desenvolver o modelo. Os modelos de ANN e análise dimensional, apresentaram erro absoluto máximo de 0.324 kPa e 1.647 kPa, respectivamente. Conclui-se que ANNs melhoraram o ajuste em relação ao modelo de análise dimensional.

Palavras-chave: microirrigação, modelo, ajuste

INTRODUCTION

Artificial Neural Networks (ANNs) are inspired by the human brain and based on mathematical models that enables capabilities of learning and storage from experimental knowledge. Artificial neurons are the constitutive units in an ANN.

A multilayer perceptron (MLP) is a feedforward ANN consisting of layers connected by synapses that can be applied on modeling functional relationships. The input layer consists of all covariates in separate neurons and the output layer consists of the response variables. The layers in-between are referred to as hidden layers, as they are not directly observable. Input layer and hidden layers include a constant neuron relating to intercept synapses, i.e. synapses that are not directly influenced by any covariate. To each of the synapses, a weight is attached indicating the effect of the corresponding neuron, and all data pass the neural network as signals. The signals are processed first by the so-called integration function combining all incoming signals and second by the so-called activation function transforming the output of the neuron (GÜNTHER; FRITSCH, 2010).

Martí et al. (2010) assessed models for estimating local head losses of integrated drippers. They compared results obtained by models based on linear regression against models based on ANNs and they concluded that models based on ANNs presented better performance on estimating local head losses.

Perboni (2012) compared a model based on multiple regression with another one based on dimensional analysis. Both models were developed for estimating the head loss along pipes accounting for in-line cylindrical emitters. The model based on dimensional analysis presented lower deviation between estimated and observed values than the model based on multiple regression.

This work proposes the use of ANNs to improve the performance of models for predicting head losses along emitting pipes accounting for cylindrical in-line emitters. In addition to the work of Martí et al. (2010), we also present an ANN's equation that enables to simulate scenarios using a spreadsheet application.

MATERIAL AND METHODS

The term hf_{Se} express the total head loss between two consecutive emitters. By this approach, data analysis is easier to perform and the model becomes easier to use. The proposed model considers that hf_{Se} is the sum of friction and local head losses (Eq. 1). Friction head loss between two consecutive emitters was expressed by the Darcy-Weisbach formula, where the pipe length (L) was replaced with the distance between two consecutive emitters (S_e). The local head loss was calculated based on Borda-Carnot equation considering the mean cross-sectional area of flow where an emitter is located (Ae_m).

$$hf_{Se} = \left[f \frac{S_e}{D_t} + \left(1 - \frac{Ae_m}{A_t}\right)^2 \right] \frac{V_t^2}{2\,g} \qquad (1)$$

Where:

hf_{Se}= total head loss between two consecutive emitters (m);

f=friction coefficient of the Darcy-Weisbach formula (-);

S_e=emitter spacing (m);

D_t=internal diameter of the pipe (m);

Ae_m=mean cross-sectional area of flow where an emitter is located (m^2);

A_t=cross-sectional area of the pipe (m^2);

V_t= mean water velocity at uniform pipe sections (m s^{-1}); and,

g=gravitational acceleration (m s^{-2}).

Eq. (2) resulted from Eq. (1) and it presents a theoretical model for estimating total head loss between two consecutive emitters, which considers the friction coefficient given by the Blasius equation.

$$hf_{Se} = \left\{\left[0.316\left(\frac{V_t D_t}{\nu}\right)^{-0,25}\frac{S_e}{D_t}\right] + \left(1 - \frac{Ae_m}{A_t}\right)^2\right\}\frac{V_t^2}{2g} \quad (2)$$

Where:
ν = kinematic viscosity of water ($m^2\ s^{-1}$).

Therefore, the following relation can be defined:

$$hf_{Se} = \emptyset(V_t, D_t, \nu, S_e, Ae_m, A_t, g) \quad (3)$$

where:
$\emptyset$ is a funcional symbol.

The variables listed in Eq. (3) are the input variables of the model and were determined by experimental means. The exception was the gravitational acceleration (g), which is a constant, and A_t that in determined based on D_t values.

The experimental data of hf_{Se}, V_t, D_t, ν, S_e was obtained from a research carried out at the Irrigation Laboratory of the Department of Biosystems Engineering, University of São Paulo, Piracicaba, Brazil. The tests were performed in a closed circuit system (Figure 1) described in detail by Perboni (2012).

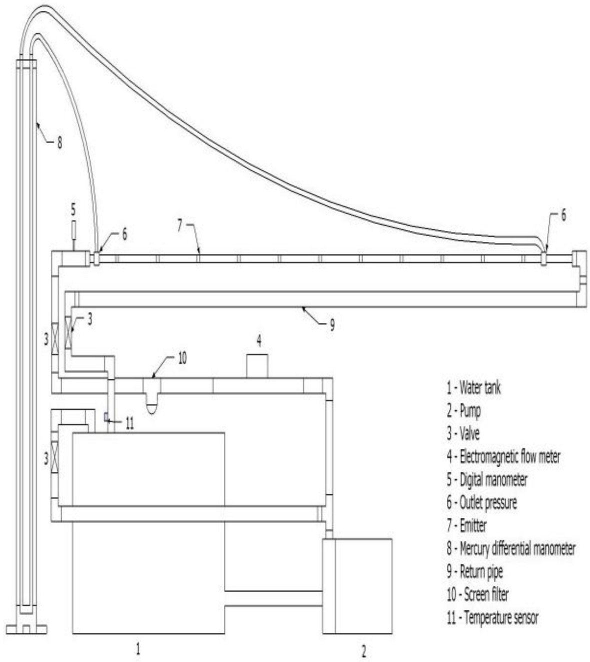


Figure 1. Schema of the facility for head loss tests.

Mean cross-sectional area of flow where an emitter is located (Ae_m) was determined indirectly based on the volume of distilled water required to fill up a cylinder of pipe wherein the emitter was assembled. Eight samples (cylinders) were extracted from each model of emitting pipe. The length of each sample was exactly the length occupied by an emitter inside the pipe. The samples were sealed at one side in order to allow filling it up with water. Samples empty and filled up with water were weighed using a digital balance (accuracy 0.01 g). The value of Ae_m of each sample resulted from the water volume inside each cylinder divided by its length. A digital caliper (accuracy 0.01 mm) was used to measure the cylinder length.

The R software (version 2.15.1) was employed to data analysis (R. DEVELOPMENT CORE TEAM, 2012). The Neuralnet package enabled implementation of artificial neural networks routines. Details about the Neuralnet package may be found at Günther e Fritsch (2010).

A multilayer perceptron with resilent backpropagation supervised learning algorithm was used for simulation of hf_{Se}. A logistic transfer function was selected between the input and hidden layers, and a logistic transfer function selected between the hidden and output layer.

The package Neuralnet enables to export the synapses weights and consequently an equation can be determined. Based on the equation, an electronic spreadsheet is enough to simulate various scenarios.

The input data were normalized from 0 to 1 (Eq. 4) to improve the efficiency of the neural network training stage.

$$x_{norm} = \frac{x_0 - x_{min}}{x_{max} - x_{min}} \qquad (4)$$

Where: x_{norm} = normalized value;

x_o = original value;

x_{max} = maximum value; and,

x_{min} = minimum value.

The dataset was randomly arranged into two subgroups. Seventy percent of the data was arrange in a subgroup for training the ANN while thirty percent of the data was kept in the other subgroup reserved for model validation.

The performance of the neural network models was evaluated by the sum of squared errors (SSE) and root mean square error (RMSE) as presented in Eq. [5] and Eq. [6], respectively.

$$SSE = \sum_{i=1}^{n}\left[\left(hf_{Se0}\right)_i - \left(hf_{Se_S}\right)_i\right]^2 \qquad (5)$$

Where, the subscripts *o* and *s* represent the observed and simulated values of head loss between consecutive emitters (hf_{Se}), respectively. The index and the total number of events are represented by *i* and *n*, respectively.

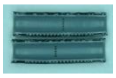
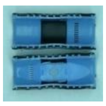
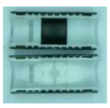
$$RMSE = \sqrt{\frac{SSE}{n}} \qquad (6)$$

The overall performance of trained networks was assessed based on the RMSE and the coefficient of determination (R^2).

RESULTS AND DISCUSSION

Model input data

Table 1. Geometric and hydraulic characteristics of the emitting pipes

Emitting pipe	Picture of emitter	L (m)	S_e (m)	D_t (mm)		Ae_m (mm²)		Relation pressure-flow rate $q_{(Lh^{-1})} = Kh^{x}_{(kPa)}$	
				$\bar{x}$	σ	$\bar{x}$	σ	k	x
1		9.80	0.98	13.60	0.15	108.74	2.13	2.048	0.064
2		10.14	0.78	13.91	0.22	105.10	1.91	2.592	-0.027
3		9.90	0.90	13.75	0.07	109.35	2.06	3.994	0.001
4		10.40	0.52	13.57	0.16	107.45	2.04	1.518	0.092
5*		10.50	0.50	13.65	0.23	110.01	1.45	0.045	0.625
6		10.36	0.74	13.49	0.18	105.76	2.14	2.722	-0.017
7		10.27	0.79	15.01	0.17	135.97	2.47	1.659	0.046
8		10.36	0.74	15.22	0.17	137.03	1.90	3.380	-0.043
9*		10.40	0.20	17.12	0.24	197.97	1.64	0.106	0.500
10*		10.20	0.60	15.67	0.37	191.46	1.76	0.132	0.520
11		10.40	0.40	14.28	0.30	187.94	1.57	1.650	0.038
12		10.50	0.30	17.30	0.39	189.96	1.64	0.644	0.072

L=Length of the emitting pipe; k and x= coefficients of the pressure-flow rate function; * =non pressure-compensating drippers.

Normalization of the input data

The data of the training subgroup was normalized following the maximum and minimum values shown in Table 2.

Table 2. Maximum and minimum values for data normalization.

	Hf_{Se} observed (m)	Se (m)	Dt (m)	Vt (m s^{-1})	V (m s^{-1})	Ae_m (m²)
Maximum	1.098	0.98	0.01730	2.80	0.00000131	0.00019797
Minimum	0.001	0.20	0.01349	0.18	0.00000066	0.00010510

Definition of the optimal ANN structure

Six runs assessing the number of neurons in the hidden layer were performed. For each condition, five repetitions were performed. Figure 2 shows an example of MLP ANN with six neurons in the input layer, three neurons in the hidden layer and one neuron in the output layer.

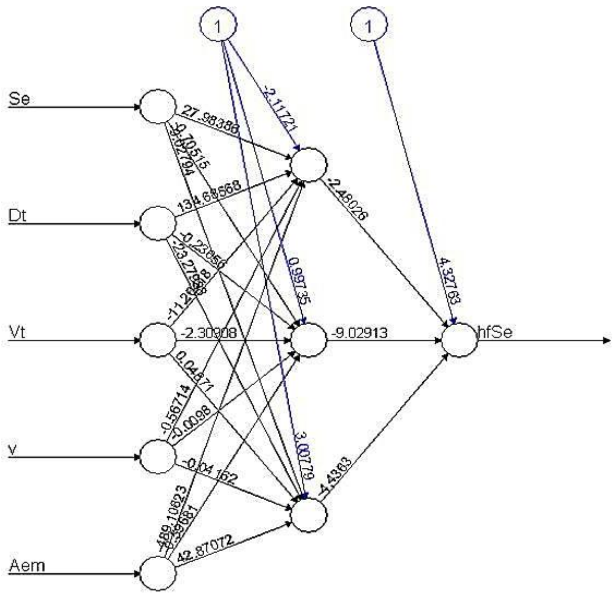


Figure 2. MLP with six neurons in the input layer, three in the hidden layer and one in the output layer.

In the Table 3 are presented the results of performance of different structures of neural networks.

Table 3. Summarized results for determining the optimal network

Network structure	SSE (m)		RMSE		R^2	
	Training	Validation	Training	Validation	Training	Validation
6-3-1	0.1835	0.4537	0.0179	0.0281	0.9944	0.9587
6-4-1	0.1482	0.0532	0.0161	0.0096	0.9955	0.9952
6-5-1	0.0722	0.0327	0.0112	0.0075	0.9978	0.9970
6-6-1	0.0804	0.0186	0.0118	0.0057	0.9975	0.9983
6-7-1	0.0364	0.0104	0.0079	0.0042	0.9989	0.9991
6-8-1	0.0580	0.0188	0.0100	0.0057	0.9982	0.9983

Comparing the network structures 6-6-1 with 6-7-1 the first one presented higher values of SSE and RMSE and smaller values R^2 for both training and validation stages. The structure 6-6-1 was preferred because of the lower complexity of the equation of this ANN structure and because of small differences with the structure 6-7-1. The weights adjusted during the training stage of the network were exported and used for generating an equation presented in Table 4.

Table 4. Syntax (Excel spreadsheet) of the artificial neural network based equation to estimate hf_{Se} (m).

hf_{Se} =0.000969230769230769+((1.09849090909091-
0.000969230769230769)*(1/(1+EXP(-(((1/(1+EXP(-
(10.7813260047022*((H10-0.2)/(0.98-0.2))+(-
40.3065786351474)*((I10-0.01348775)/(0.017299-
0.01348775))+((J10-0.184369984370609)/(2.80151262245965-
0.184369984370609))*0.104821757020942+(-
0.0874513828307588)*((K10- 0.00000066)/(0.00000066))+(-
81.9027365883784)*((L10-
0.000105104816706743)/(0.000197973869026579-
0.000105104816706743))+(-
1.62990957971955)))))*5.51777399375251)+((1/(1+EXP(-
(7.42742967425067*((H10-0.2)/(0.98-0.2))+(-
4.11228961882758)*((I10-0.01348775)/(0.017299-
0.01348775))+((J10-0.184369984370609)/(2.80151262245965-
0.184369984370609))*(-1.15292854653071)+(-
0.0881370123739626)*((K10-0.00000066)/(0.00000131-
0.00000066))+(-95.5149154978041)*((L10-
0.000105104816706743)/(0.000197973869026579-
0.000105104816706743))+(-0.405057418373449)))))*(-
5.25710864729487))+((1/(1+EXP(-
((1.18370865413044)*((H10-0.2)/(0.98-0.2))+(-
9.82653078464961)*((I10-0.01348775)/(0.017299-
0.01348775))+((J10-0.184369984370609)/(2.80151262245965-
0.184369984370609))*(-2.0030561488858)+(-
0.0383213504652739)*((K10-0.00000066)/(0.00000131-
0.00000066))+11.7616535985439*((L10-
0.000105104816706743)/(0.000197973869026579-
0.000105104816706743))+(1.41681221975827)))))*(-
3.86750206180446))+((1/(1+EXP(-(0.558087626804475*((H10-
0.2)/(0.98-0.2))+0.496913927891842*((I10-
0.01348775)/(0.017299-0.01348775))+((J10-
0.184369984370609)/(2.80151262245965-
0.184369984370609))*10.8092200112521+0.131769857529378
*((K10-0.00000066)/(0.00000131-0.00000066))+(-
1.13103785514986)*((L10-
0.000105104816706743)/(0.000197973869026579-
0.000105104816706743))+(-
2.20007430865564)))))*2.32240827563296)+((1/(1+EXP(-
(2.8789398398758*((H10-0.2)/(0.98-0.2))+(-
1.0991457746721)*((I10-0.01348775)/(0.017299-
0.01348775))+((J10-0.184369984370609)/(2.80151262245965-
0.184369984370609))*2.74862311919179+0.039153969866697
6*((K10-0.00000066)/(0.00000131-
0.00000066))+2.08759495690066*((L10-
0.000105104816706743)/(0.000197973869026579-
0.000105104816706743))+(-
7.78232584891977)))))*30.4517568304332)+((1/(1+EXP(-((-
1.09055922734043)*((H10-0.2)/(0.98-
0.2))+1.1305534378051*((I10-0.01348775)/(0.017299-
0.01348775))+((J10-0.184369984370609)/(2.80151262245965-
0.184369984370609))*0.0204773450992123+0.2499722128513
87*((K10-0.00000066)/(0.00000131-0.00000066))+(-
1.69502293148182)*((L10-
0.000105104816706743)/(0.000197973869026579-
0.000105104816706743))+1.61949546756514))))*(-
0.00255897002824903))+(-1.3362295870735))))))

Where: H10 represents S_e, m; I10 represents D_t, m; J10 represents V_t, m s^{-1}; K10 represents ν, m^2 s^{-1}; L10 represents Ae_m, m^2.

The equation takes into account the normalization of input data and it is valid for the range of values presented in Table 2, which were obtained from head loss tests.

Model validation

Based on the subgroup reserved for validating the model, the absolute maximum error between estimated and observed values of head loss was 0.033 m (Figure 3A). Such a value was lower than that obtained by the model developed by Perboni (2012), which was 0.1682 m (Figure 3B).

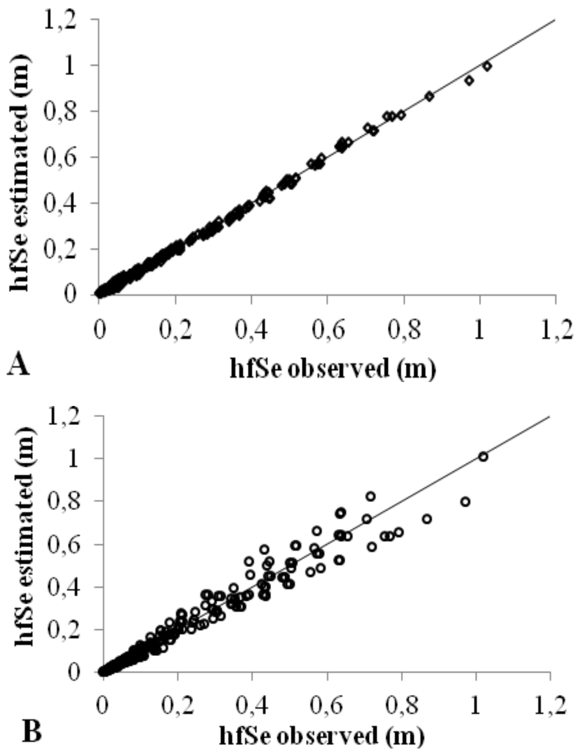


Figure 3. A) ANN model; B) Perboni (2012) model.

The ANN based equation presented better results than those obtained by an equation based on dimensional analysis (PERBONI, 2012). Although ANNs are more complex than other methodologies for fitting models, it is possible to present an equation that can be implemented in an electronic spreadsheet like Excel and consequently the predictions can be done easily.

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