

# NONLINEAR MODEL OF A RICE DRYING PROCESS USING NEURAL NETWORKS

## MODELO NO-LINEAL DE UN PROCESO DE SECADO DE ARROZ USANDO REDES NEURONALES

José Aldemar MUÑOZ, PhD.<sup>1</sup>; Carlos Arturo SÁNCHEZ, MSc.<sup>1</sup>; Helmer MUÑOZ, PhD.<sup>2, 1\*</sup>

Received: May 31 of 2018. Approved: November 29 of 2018.

### ABSTRACT

**Background:** The production quality of rice is highly depended on the drying process as drying weakens the rice kernel. A look at the production process of rice in the industry was taken. The drying of rice influences the storage capacity of the grain, the energy consumption, the final mass of the grain and the percentage of whole grains at the end of the process. **Objective:** The main objective was to analyse the drying of rice by making an artificial neural network to model and simulate it. **Methods:** The modeling of a rice drying process using neural networks was presented. These models are suitable to be used in combination with model-based control strategies in order to improve the drying process. The implementation, preprocessing and data retrieval for the design of an artificial neural system was analyzed. Controlling the drying factors is of major importance. Feedforward and dynamic neural networks were compared based on their performance. **Results:** It was concluded that when some part of the dataset is given as training, even with one dataset, a back-propagation network simulates very well the other parts of the drying curve. It can be said that the approximations done by the networks to obtain a nonlinear model of the rice drying process are quiet good. **Conclusions:** Firstly, because of the too little data available for training, the networks were not as good as expected. More data is needed to really have a powerfull network capable of approximated very well the drying curve. Secondly, a backpropagation network can be a good solution for modelling and for use in a controller if more data is available, in contrast a linear network gave bad results. thirdly, a network with little number of layers is the best option. A perfect mapping from the input to the output is impossible due the differences in each test and the imperfect sensors.

**Keywords:** drying, rice, modeling, neural networks, nonlinear.

### RESUMEN

**Antecedentes:** la calidad de producción del arroz depende en gran medida del proceso de secado, ya que el secado debilita el grano de arroz. Se estudió el proceso de producción de arroz en la industria. El secado del arroz influye en la capacidad de almacenamiento del grano, el consumo de energía, la masa final del grano y el porcentaje de granos totales al final del proceso. **Objetivo:** El objetivo principal fue

---

<sup>1</sup> Ingeniería Agroindustrial, Universidad del Tolima. Ibagué, Colombia

<sup>2</sup> Programa Contaduría Pública, Universidad del Sinú. Montería, Colombia

\* Autor de correspondencia [helmermunoz@unisinu.edu.co](mailto:helmermunoz@unisinu.edu.co)

analizar el secado del arroz diseñando una red neuronal artificial para modelarlo y simularlo. **Métodos:** Se presentó el modelado de un proceso de secado de arroz utilizando redes neuronales. Estos modelos son adecuados para ser utilizados en combinación con estrategias de control basadas en modelos para mejorar el proceso de secado. Se analizó la implementación, el pre-procesamiento y la recuperación de datos para el diseño de un sistema neuronal artificial. Controlar los factores de secado es de gran importancia. Las redes neuronales avanzadas y dinámicas se compararon en función de su rendimiento. **Resultados:** se llegó a la conclusión de que cuando una parte del conjunto de datos se proporciona como entrenamiento, incluso con un conjunto de datos, una red de propagación inversa simula muy bien las otras partes de la curva de secado. Las aproximaciones hechas por las redes para obtener un modelo no lineal del proceso de secado del arroz son bastante buenas. **Conclusión:** En primer lugar, debido a la poca información disponible para el entrenamiento, las redes no fueron tan buenas como se esperaba. Se necesitan más datos para tener realmente una red potente capaz de aproximar muy bien la curva de secado. En segundo lugar, una red de propagación hacia atrás puede ser una buena solución para modelar y usar en un controlador si hay más datos disponibles, en contraste, una red lineal arrojó malos resultados. En tercer lugar, una red con poca cantidad de capas es la mejor opción. Un mapeo perfecto de la entrada a la salida es imposible debido a las diferencias en cada prueba y los sensores imperfectos.

**Palabras clave:** secado, arroz, modelado, redes neuronales, no lineales.

## INTRODUCTION

Rice is of great importance for Colombia because it is the second largest rice producer in Latin America and the Caribbean. Rice occupies the first place in terms of economic value among short-cycle crops and is the primary source of calories and protein for the low-income group; which accounts for about 20% of the country's population. The national average per capita rice consumption in 2000 was 45.3 kg of brown rice. In addition to local production, Colombia even has to import additional rice to meet demand.

Rice is an important food source which should be at low moisture content for safe storage. Unfortunately, the moisture content of rough rice after harvesting is about 24% dry basis, which encourages the growth of molds (1). In order to conserve the rice in a proper way the moisture content has to be near 14% dry basis (2). A topic of economic importance related to the drying process is the cracking of the rice kernel. Larger grains are more expensive than smaller grains, so it is important to prevent cracking. This can only be done if the drying process is carried out in stages with a certain temperature and air velocity. Another factor that limits the maximum temperature is the degradation of the quality of the grain due to increased enzymatic inactivation (1). Because of the sensitivity of the rice and since rice drying is an energy-intensive process; increasing the efficiency of the drying process has important economic consequences for both rice producers and for consumers.

A simple model with a simultaneous heat and mass transfer during rice drying in a deep-bed was developed in (3). The drying process can be divided into three different stages: Dynamic drying, fixed bed drying and removing the internal stress, we focus on the Fixed bed drying part of the process which can be approximated by a curve like in Figure 1(4); as rice is a hygroscopic material.

### Physical models

In order to understand the drying process physically, it is necessary to see how the moisture content is evolving in time inside the plenum as well as inside the rice kernel. To accomplish this plenum is divided in thin layers which are consisting of single rice kernels.

The rice kernel on its own is a very complex biological grain, so a simplification has to be made. The grain is taken as a non-axially symmetrical ellipsoid divided into three layers: hull, bran and endosperm. The drying process itself is dominated by convective heat and mass transfer, so neglecting of conduction does not result in a significant error. Based on the above assumptions, the three-dimensional governing equations [1, 2] in a Cartesian coordinate system can be expressed as:

$$\begin{aligned} \rho_g c_g \frac{\partial T}{\partial \tau} &= k \left( \frac{\partial^2 T}{\partial x^2} + \frac{\partial^2 T}{\partial y^2} + \frac{\partial^2 T}{\partial z^2} \right) \\ \frac{\partial M}{\partial \tau} &= D \left( \frac{\partial^2 M}{\partial x^2} + \frac{\partial^2 M}{\partial y^2} + \frac{\partial^2 M}{\partial z^2} \right) \end{aligned} \quad (1)$$

Boundary conditions:

$$-k \frac{\partial T}{\partial n} = h_t(T - T_a), -D \frac{\partial M}{\partial n} = h_m(M - M_e) \quad (2)$$

Where,

T is temperature in °C; M is the moisture content in % dry basis [d.b]; D is the diffusion coefficient in m<sup>2</sup>s<sup>-1</sup>; k is the thermal conductivity in W m<sup>-1</sup> °C<sup>-1</sup>; τ is the time in s; r<sub>g</sub> is the kernel density in kgm<sup>-3</sup>; c<sub>g</sub> is the rice specific heat capacity in J kg<sup>-1</sup>°C<sup>-1</sup>.

Initial conditions: when τ = 0,

$$M = M_0 \text{ and } T = T_0$$

To get a numerical solution to this partial differential equation (second order linear partial differential equation) that is close to the real solution, it is necessary to have an accurate numerical representation of the boundary conditions.

To solve the PDE it is necessary to specify the initial and boundary conditions. Between the existing numerical methods, probably the most used in the PDE solution is the method of finite differences. In this kind of problems, the solution moves forward indefinitely from known initial values, always satisfying the boundary conditions. The basic concept of the method is relatively simple, but the implementation is often complex (5). The procedure is to discretize the domain of integration of the PDE by using a mesh discretizing the PDE and its conditions, obtaining algebraic equations for each node (such nodal equations are related in a way that a system of equations algebraic is obtained), and finally write a program to solve the system of algebraic equations. Algebraic system solution represents the values of the PDE solution.

Many researchers have modeled thin layer drying using Fick's law or empirically desire equations (6). In the works of (7-10) appear results on computer base grain drying control systems. Although these models provide fast data acquisition during complex experimental conditions and versatility

of operations through software control, they presented several implementation complexities.

In (11) four thin-layer equations were derived by regression analysis to predict the drying behavior for deep-bed drying of rough rice. The effects of drying air temperature, drying air absolute humidity, drying time interval, and tempering time interval were considered.

These mathematical models presented several complexities which increase the computational cost. On another hand they use several approximations that decrease the performance of the models. Hence, if they must be used in combination with model-based control strategies, faster and more accurate models have to be used. That is why nonlinear models based on artificial neural networks are explored.

In this paper supervised neural network topologies was used. Artificial neural networks (AANs) were used for the prediction of equilibrium moisture content of three varieties of paddy (Caribe -8, Orizica -1, Yacu -9), (12), Authors used to feed forward back-propagation and cascade forward backpropagation networks with Levenberg-Marquardt and Bayesian regularization training algorithms to train the input data patterns.

The algorithm was developed using Matlab/Simulink, some related information can be found in (13, 14). In (15) a feed-forward neural network topology is presented to model the non-linear drying process and it uses a multilayer perceptron for modeling the drying of the production of a coconut process and in (16) modeling and control of drying process using neural networks is presented.

### Dynamic Neural Networks

Unlike the feedforward network, where there is an algebraic relationship between input and output, this architecture contains memory. There is feedback on the output and the inputs have a certain delay. The basic equation of the network is:

$$\hat{y}(t) = F_i \sum_{j=1}^{n_h} W_{i,j} f_i \sum_{l=1}^{n+m} w_{j,l} \phi_l(t) + F_i \sum_{j=1}^{n_h} W_{i,j} f_i \sum_{l=1}^{n_h} w_{j,l} f_i(r, t-1) + w_{j,0} + F_i W_{i,0} \quad (3)$$

In Figure 1 the topology of a dynamic neural network is presented (14). A Narx topology of the dynamic neural network is presented in this paper. There are two different versions of Narx topologies. The parallel architecture feeds the predicted output signal back to the input latter. The series-parallel architecture uses the measured

output signal as input. The latter will be used for the following reasons: a) The input to the feedforward architecture is more accurate because it is the real measured output signal, and b) A second advantage is that the resulting network has a pure feedforward architecture, which allows static backpropagation to train it.

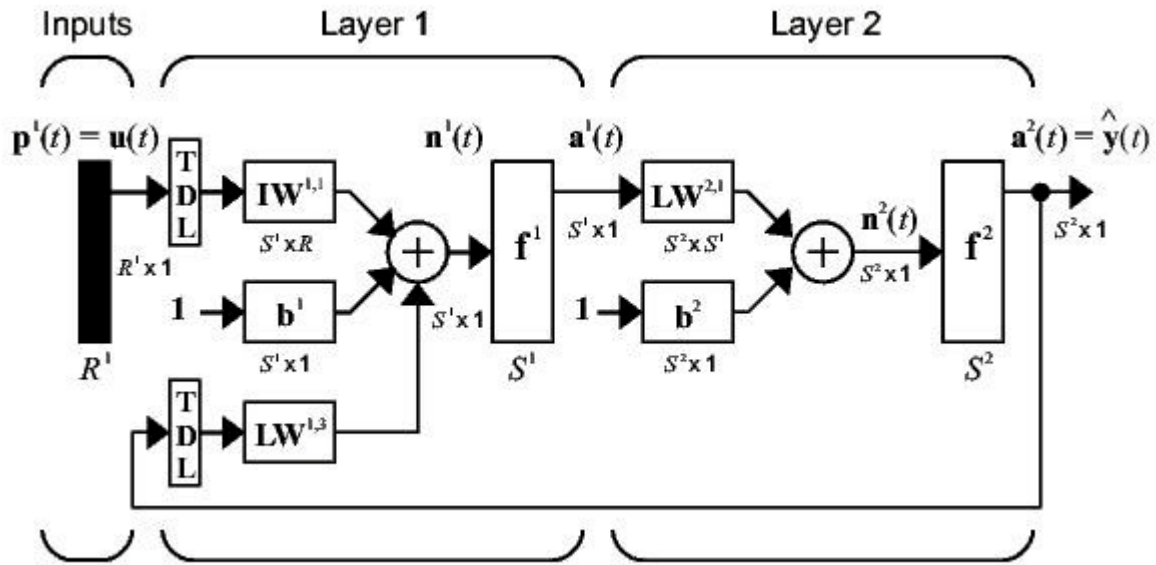


Figure 1. Topology of a series-parallel nonlinear neural ARX model (NARX).

A general way of looking at the efficiency of embedding a problem in a neural network comes from a computational complexity point of view. Solving a problem on a sequential computer requires a certain number of steps (times complexity), a certain memory size (space complexity), and a certain length of the algorithm. The several topologies of the neural NARX neural networks can be seen in Figures 1 and 2 (14).

energy performance of the process is presented. (18) an optimal multi-layered, feed-forward, artificial neural network (MLFF-ANN) model for predicting the moisture ratio of paddy during the drying process was investigated.

## MATERIALS AND METHODS

### Physical Plant

There is a scale model of the fixed bed inclined floor dryer. In the inclined floor furnace, hot air, generated by a fan and a heating resistance, is blowing from under the rice upwards through the plenum. In order to model and control the process, there are two thermocouples to measure the temperature of the rice, another one to control the air temperature and a moisture content sensor to determine the humidity of the rice. The airflow and the air temperature are the parameters that can be adapted to control the process, but in industrial applications only the air temperature is

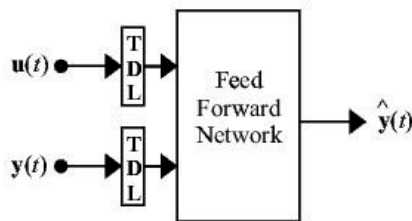


Figure 2. Series-parallel architecture of NARX.

In (17) the kinetics of convective deep-bed drying of rough rice using NN to study the

variable. The temperature is adapted by a Pulse Width Modulated resistance regulated by a PID controller with integrated anti-windup to prevent accumulation of the integration error which is caused by the slow temperature time constant. The air flow can be regulated by a frequency modulated scalar control. Measurements are collected by a Labview-program, but the model and the control of the drying process are implemented in Matlab. To carry out the experiments a thin layer dryer was tested. Figure 3 shows the prototype of the system to identify:

1) Pressure meter transformer; 2) Heating resistance; 3) Electrical transformer; 4) Electric circuit of the resistance; 5) Electronic controller of the plant; 6) Differential pressure meter; 7) Differential pressure meter; 8) Ball valve; 9) Ball valve; 10) Fan.



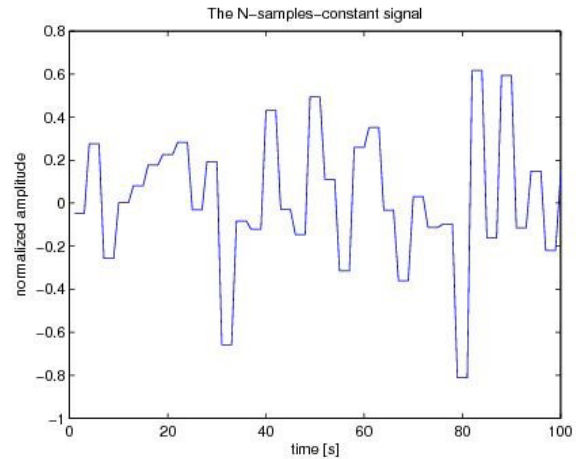
**Figure 3.** The plant lay-out identification of the nonlinear system.

### Experimental setup

To identify the nonlinear system, some signals have to be selected. The following signals were chosen for this purpose.

- **N-Samples-Constant.** If  $e(t)$  is a white noise signal; the N-sample-constant signal (Figure 4) is defined by:

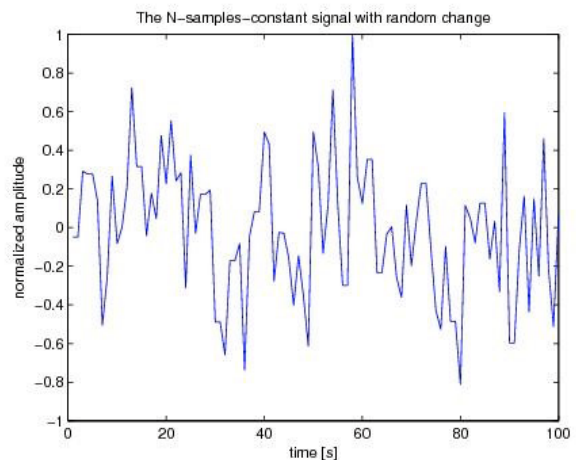
$$u(t) = e\left(\text{int}\left[\frac{t-1}{N}\right] + 1\right), \quad t = 1, 2, \dots \quad (4)$$



**Figure 4.** The N-samples-constant signal.

- **Level change at random instance.** This is an extension to the N-samples-constant. Another random variable (Not a predefined integer) will decide when to change the level of the input signal (Figure 5).

$$u(t) = \begin{cases} u(t-1) & \text{with probability } \alpha \\ e(t) & \text{with probability } 1-\alpha \end{cases} \quad (5)$$



**Figure 5.** The N-samples-constant signal with a random change.

- **Chirp signal.** A chirp signal is a signal in which the frequency increases with time (Figure 6). With this signal, it is possible to excite the desired frequency range. When applying this

signal to a nonlinear system, different DC-values, and amplitudes have to be taken.

$$w_t = w_{start} + \frac{t}{N}(w_{final} - w_{start}) \quad (6)$$

$$u(t) = u_0 + Aa \sin(w_i t T_s) \quad t=1, 2, \dots \quad (7)$$

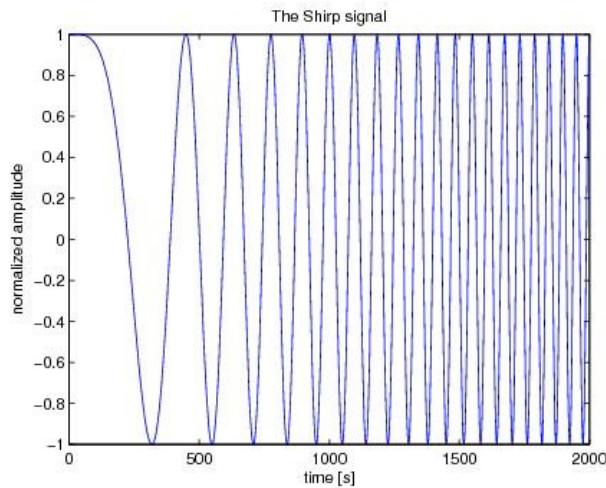


Figure 6. The Chirp signal.

- **System Bandwidth.** The bandwidth is a representation of the response time of the system. Experiments were conducted at two drying air temperatures and the airspeed remained at a constant level because it is shown that air velocity only has a very weak dependence of moisture ratio. In order to get this response time, the following test is performed: Test 1 (Air temperature: 40°C, 7 hours), Test 2 (Air temperature: 35°C, 33 hours).

At the transition, there is a transient that is characterizing the bandwidth. To determine the length of this transient a curve fitting was performed as can be seen in Figure 7. The fitted curves and the filtered version of the original test data are compared. Clearly, the transient is approximately 2.5 hours. As a linear approximation of the system a first-order dynamic is proposed:  $\frac{1}{\tau s + 1}$ , where  $1/\tau$  corresponds to the bandwidth. The rule of Thumb says that the reaction time of the system (2.5 h) is five times  $\tau$ , such that the bandwidth equals 1/1800 Hz.

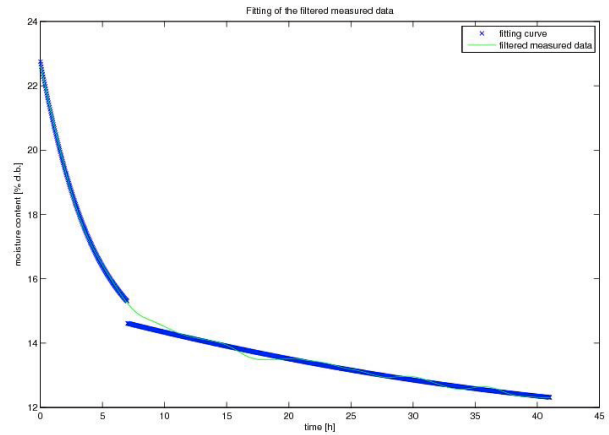


Figure 7. The fitting of the moisture content.

## RESULTS AND DISCUSSION

In this section, the results for the feed forward back-propagation and the dynamic neural networks topologies are presented.

### Feed Forward Back-Propagation Neural Network

In Figure 8 the response of the feedforward back-propagation neural network to validation data is compared with the original data. As can be seen, the results follow some of the dynamics of the system, however, the predictive curve is totally out of the range of the real data.

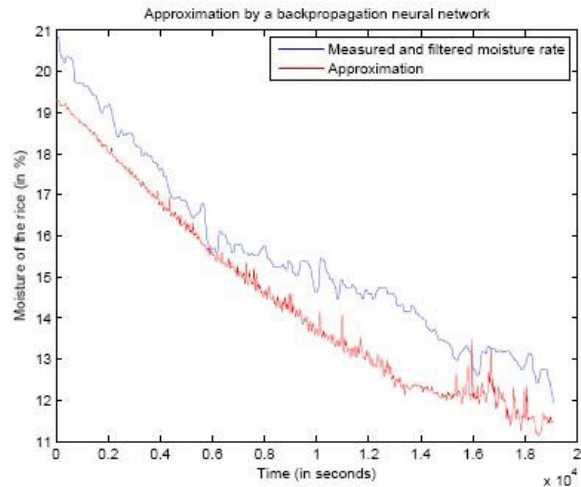
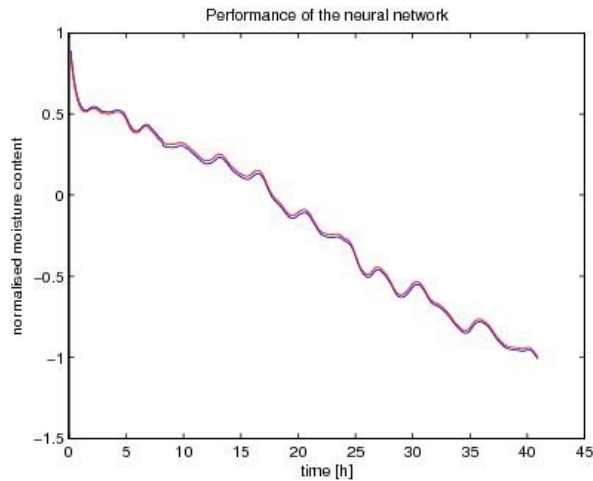


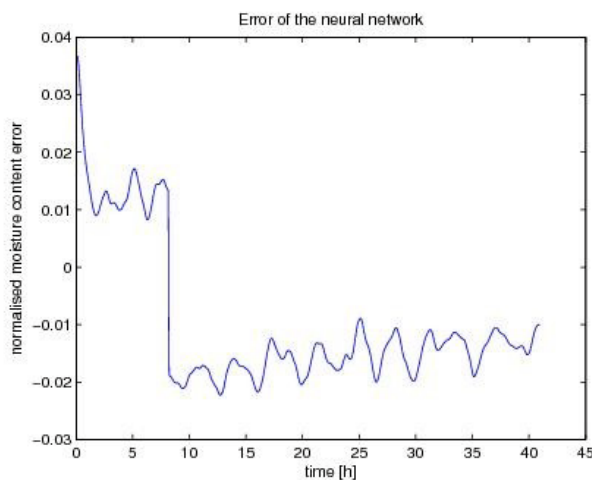
Figure 8. Validation data (red) vs real data (blue) from a test experiment using feedforward back-propagation neural networks topology.

## Dynamic Neural Network

In Figure 9 the response of the Dynamic Neural Network to validation data is compared to the original data. As can be seen, the result follows almost perfectly the dynamics of the process. In Figure 10 the error between the predicted and the real values of the moisture are presented.



**Figure 9.** Validation data (red) vs real data (blue) from a test experiment using dynamic neural networks topology.



**Figure 10.** Error between predicted and real values in a test experiment using a dynamic neural network.

When generating a new neural network using datasets for training, the result of the network always has to be checked, because they are non-deterministic, so sometimes the result after the training can be very bad; the network is useless and training has to be done again. A network

with a lot of layers does not especially gives the best result. A short network has the advantage of needing less training computations. Optimizing all the network parameters is a time consuming task; everytime a parameter is changed, the network has to be trained again. In general, it can be said that the approximations done by the networks to obtain a nonlinear model of the rice drying process are quiet good. They can be a lot better if more datasets for training are available.

Sometimes the training of the network stops before a good network appears, the reinitialization and training of the network must be done again. In general, the biggest problem of the project realization is the little available data for training and simulating the network. Using big networks with a lot of layers results in a lot of calculations, this is also an important factor that has to be taken into account. It can also be concluded that when some parts are given as training, even with one dataset, a back-propagation network simulates very well the other parts of the drying curve. Advantages of this strategy can be seen in (19), where an independent multilayer neural network approach was used to predict the performance of the dryer for drying of rice, and in (20), where by applying the artificial neural networks (ANNs), moisture content of paddy was predicted under the various input conditions.

## CONCLUSIONS

This paper presents an application of artificial neural network (ANN) technique to develop a model representing the non-linear drying process. The air heat plant (AHP), an important component in drying process is fabricated and used for building the ANN model. An optimal feed forward neural network topology is identified for the air heating system set-up. The training sets are obtained from experimental data. Back-propagation algorithm with momentum factor is used for training. The results show that the back-propagation ANN can learn the functional mapping between input and output. The advantages of ANN model developed for AHP is highlighted. The developed model can be used for control purposes.

The neural networks are suitable for modeling nonlinear systems. However, some things have to be taken into account; the training data have to be selected in such a way that all the information

related to the dynamic of the process is presented; the number of layers and the kind of activation function has to be selected in a proper manner, in order to obtain the best configuration as possible. Some topologies include also grain temperature for better performance.

On another hand, the characteristics of the process will lead us to the selection of a topology of the neural network. In this work, the memory present in the drying process affects the performance of the simple feed forward back-propagation neural network. The dynamic neural network, on the contrary, feeds the output of the system, has the capacity to act based not only in the present data but also on the past input and outputs. For this reason, the performance of the dynamic NN is much better compared with the other topology.

### CONFLICT OF INTEREST

The authors certify that there is no conflict of interest in this research.

### ACKNOWLEDGEMENTS

The authors would like to thank the University of Tolima, the University of Leuven-Belgium and the University of Sinù Elías Bechara Zainúm for the support with students in internship and financial support. Likewise, the University of Ibagué is praised for the contribution of the drying equipment where the tests were carried out.

### AUTHORS' CONTRIBUTIONS

The authors declare contribution in the same proportion for the development of the investigation and the elaboration of the article.

### REFERENCES

1. Srivastava V, John J. Deep bed grain drying modeling. *Energy conversion and management*. 2002;43(13):1689-708.
2. Chen C, Wu P-C. Thin-layer drying model for rough rice with high moisture content. *Journal of Agricultural Engineering Research*. 2001;80(1):45-52.
3. Garreiro JM, Kahan S, Zecchi B, Gerla P, Clavijo L, Rodríguez A, editors. *A SIMPLE MODEL FOR RICE GRAINS IN A DEEP-BED DRYER*. 4th MERCOSUR Congress on Process Systems Engineering; 2nd MERCOSUR Congress on Chemical Engineering: Proceedings of ENPROMER 2005; 2005; Rio de Janeiro. 1 p.
4. Brooker DB, Bakker-Arkema FW, Hall CW. *Drying cereal grains*. 4 ed. USA: American Association of Cereal Chemists; 1992.
5. Eckert ERG, Drake Jr RM. *Analysis of heat and mass transfer*. 1987.
6. Thompson T, Peart R, Foster G. Mathematical simulation of corn drying—a new model. *Transactions of the ASAE*. 1968;11(4):582-0586.
7. Stone M, Kranzler G. A microprocessor controlled thin-layer dryer [Down-draft-cross-flow design]. Paper-American Society of Agricultural Engineers (Microfiche collection)(USA) No fiche No 81-5028. 1981.
8. Wafler P, Warnock W. A microprocessor controlled crossflow grain dryer test unit [Monitors dry bulb and dew point temperatures, hardware, software]. Microfiche collection. 1982.
9. Mittal G, Otten L. Microprocessor controlled low-temperature corn drying system. *Agricultural Systems*. 1983;10(1):1-19.
10. Omid M, Yadollahinia A, Rafiee S, editors. *A thin-layer drying model for paddy dryer*. Proc of the International conference on Innovations in Food and Bioprocess Technologies, AIT, Pathumthani, Thailand, 12th; 2006. 202-11 p.
11. Liu X, Chen X, Wu W, Peng G. A neural network for predicting moisture content of grain drying process using genetic algorithm. *Food Control*. 2007;18(8):928-33.
12. Amiri Chayjan R, Moazez Y. Estimation of paddy equilibrium moisture sorption using ANNs. *Journal of Applied Sciences*. 2008;8:346-51.
13. Freeman JA, Skapura DM. *Algorithms, applications, and programming techniques*: Addison-Wesley Publishing Company, USA; 1991. 414 p.
14. Demuth H, Beale M. *Neural Network Toolbox For Use with Matlab--User'S Guide Version 3.0*. 1993.
15. Thyagarajan T, Panda R, Shanmugan J, Rao V, Ponnaivaikko M. Development of ANN model for non-linear drying process. *Drying technology*. 1997;15(10):2527-2540.
16. Tohidi M, Sadeghi M, Mousavi SR, Mireei SA. Artificial neural network modeling of process and product indices in deep bed drying of rough rice. *Turkish Journal of Agriculture and Forestry*. 2012;36(6):738-748.
17. Beigi M, Torki-Harchegani M, Tohidi M. Experimental and ANN modeling investigations of energy traits for rough rice drying. *Energy*. 2017;141:2196-205.
18. Chokphoemphun S, Chokphoemphun S. Moisture content prediction of paddy drying in a fluidized-bed drier with a vortex flow generator using an artificial neural network. *Applied Thermal Engineering*. 2018;145:630-636.
19. Alam MA, Saha CK, Alam MM, Ashraf MA, Bala BK, Harvey J. Neural network modeling of drying of rice in BAU-STR dryer. *Heat and Mass Transfer*. 2018:1-9.
20. Thant PP, Robi P, Mahanta P. ANN Modelling for Prediction of Moisture Content and Drying Characteristics of Paddy in Fluidized Bed. *International Journal of Engineering and Applied Sciences (IJEAS)*.3(3):118-23.