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Digital Transformation in Mini Power Plants: Optimization of Hydroelectric Turbines with Neural Networks

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Abstract:* This research aimed to optimize the parameters of hydraulic turbines using artificial neural networks (ANNs) in a mini power plant operating with various water volumes. Several phases were conducted, including data collection of flow rate, water head, and rotation speed (rpm), which were tabulated and utilized to train the ANNs. An intelligent system based on ANNs was implemented, consisting of three input layers and five output layers using the backpropagation algorithm. Additionally, an instruction sequence was designed, and the ANNs were trained using NeuroShell 2 software. The selection of turbines was performed by the intelligent system based on expert knowledge and previous calculations. The results obtained showed significant accuracy in predicting power (in HP and KW), impeller type, and output speed (rpm), ensuring stable and reliable values of electrical energy for the mini hydroelectric plant. In conclusion, this study highlights the effectiveness of neural networks in optimizing hydroelectric turbines, emphasizing their importance in improving efficiency and reliability in electricity generation.

Keywords: *artificial neural network, backpropagation, hydraulic turbine, hydroelectric power plant*

I. INTRODUCTIÓN

Current changes in climate patterns can alter water availability, affecting both the quantity and quality of water resources. The energy industry must adapt to these changing conditions to ensure a constant supply of water for uninterrupted energy production [1]. Studies on renewable energy suggest investing in advanced generation technologies to improve the efficiency of energy production and at the same time reduce the environmental impact.

With a growing population and increasing industrialization, the demand for water is outstripping its availability in many regions. According to the United Nations, by 2040, more than 20% of the world's population will be affected by water scarcity, posing a significant challenge for the energy industry that requires innovative solutions to mitigate its impact on energy production [2].

Given the current situation, digitalization emerges as a crucial pillar in the progress of hydroelectric efficiency. Constant monitoring is supported by intelligent systems that perform predictive statistical analyzes with exceptional precision, making it possible to optimize plant performance by installing the most appropriate turbines.

In Peru there are different rivers with different constant and abundant flows, which can be used for the production of clean electrical energy, by appropriately selecting the parameters of the turbines. According to [3] about 1,700 MW that Enel Generation produces in the Andean nation, 47% is derived from the exploitation of water energy that feeds eight plants, six of which are located in the Lima region.

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The main objective of this research is to use the backpropagation algorithm together with the NeuroShell 2 software to train an Artificial Neural Network (ANN). This is carried out in order to achieve accurate predictions and effective pattern classification, with the specific purpose of ensuring that the mini hydropower plant uses the most suitable turbines to generate an installed power of less than 10 MW.

The proposed hypotheses suggest that using real data and the NeuroShell 2 software, it is possible to predict significant results for the selection and calculation of parameters of a hydraulic turbine. This is achieved by including input variables such as water height and flow.

Currently, in the Peruvian context, the application of this model is beginning. Therefore, it is crucial to obtain experience that enriches the hydraulic turbine selection process. This involves precisely considering the actual input parameters and the learning capacity of the ANN. In this way, adequate energy production results can be obtained, in accordance with standards and protocols established in the design of the analytical method for turbine selection [4][5].

II. STATE OF THE ART

From the point of view of an adaptive machine, it is a massively parallel distributed processor composed of simple processing units, which naturally tend to store experimental knowledge and make it available and usable. An artificial neural network (ANN) is similar to the brain in two aspects:

- The network acquires knowledge from its environment through a learning process and
- The connection weights between neurons, known as synaptic weights, are used to store acquired knowledge. [6] [7]

Neural networks using back propagation learning have shown good results in various types of problems. However, the choice of basic parameters, the network topology, the learning rate and initial weights, frequently determine the training process. Consequently, the selection of these parameters sometimes depends on the use of practical rules, however, the values that are taken are the most important to successfully solve the problem.

The development of artificial neural networks, or simply "neural network," was motivated by the analysis of how the human brain computes, which is substantially different from the digital processing of a computer [8].

Regarding learning through neural networks [9] defines this type of learning in the context of a neural network as a process by which the free parameters of a neural network are adapted to a stimulation process by the environment in which it is located. finds. Consequently, the type of learning is determined by the way in which parameter changes are made.

According to [10], the learning process involves the following sequence of events.

a. The neural network is stimulated by an environment
b. The neural network experimentally changes its free parameters as a result of stimulation.
c. The neural network responds in a new way to the environment due to changes in the internal structure.

Consequently [11] maintains that the main learning rules for the design of neural networks are:

a. Error correction learning, which tries to find an optimal filter.
b. Memory-based learning operates by memorizing the
c. training data explicitly.
d. Hebbian learning, inspired by neurobiological considerations with unsupervised self-organized learning rules.
e. Competitive learning, also inspired by neurobiology.
f. Boltzmann learning, based on statistical mechanisms

Regarding the network architecture [12] describes the way in which neurons of an artificial neural network (ANN) are structured and according to [11] they demonstrate that the network is linked to the learning algorithm used to train the network. However, sometimes we talk about learning algorithms (rules) used in the design of neural networks (structures).

The selection of a network is made based on the characteristics of the problem to be solved. Most of them can be classified into Prediction, Classification, Association, Conceptualization, Filtering and Optimization applications. The first three types of applications require supervised training [13].

The research uses prediction, in this regard [12] [13][14] explain that in the real world there are many phenomena of which we know their behavior through a time series of data or values. Lapedes and Farber of the Research Laboratory have shown that network backpropagation outperforms conventional linear and polynomial prediction methods for chaotic time series by an order of magnitude.

The invention of the Backpropagation algorithm has played a vital role in the resurgence of interest in artificial neural networks. Backpropagation is a method for training multilayer networks as shown in Fig. 1. Its power lies in its ability to train hidden layers and thus overcomes the restricted possibilities of single-layer networks [12] [13].

The main advantage of the Backpropagation network is its generic pattern mapping capability. The network is capable of learning a wide variety of pattern mapping relationships. It does not require mathematical knowledge of the function that relates input patterns and output patterns. Backpropagation only needs mapping examples to learn. The flexibility of this network is increased with the possibility of choosing the number of layers, interconnections, processing units, learning constant and data representation. As a result of these characteristics the Backpropagation network is able to successfully participate in a wide range of applications [12] [13].

Regarding hydraulic energy, this is considered a renewable energy that has the great advantage of being obtained through water stored in rivers and in natural spaces, and which constitutes 7% of global consumption [15]. These dams allow water to fall from high or not so high points, which passes through different hydraulic turbines that produce hydraulic energy.

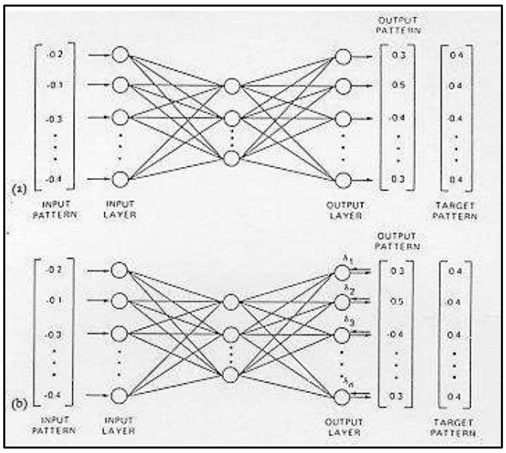


Fig. 1 Structure of the Backpropagation network [12] [13]

To describe the characteristics of a turbine according to [16] it is important to point out the parts of a hydroelectric plant, which are:

a. A dam that can be opened and closed to control the flow of water
b. A turbine, which makes them move and,
c. A generator to produce electricity.

The general scheme of an installation to generate hydroelectric energy corresponds to that indicated in Fig. 2.

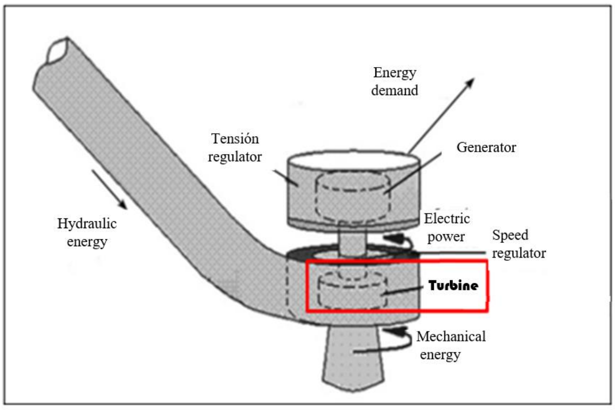


Fig. 2 Energy conversion process [17].

Fig. 2 shows that the conversion process is dynamic, the hydraulic energy is transformed into mechanical energy by the turbine and this in turn is transformed into electrical energy by a generator [17].

The research proposes the development of a computational algorithm, using neural networks, for the selection and sizing of the different hydraulic turbines, whose advantage is to reduce dependence on generation and replace other polluting sources.

Regarding a hydraulic turbine, it works when it is placed fixed in a place where water flows or there is a fall. When the liquid passes through the turbine, the rotor blades suffer a pressure drop that drives them and causes the turbine to rotate. There are three types of turbines for these heights and flows, Fig. 3. [18][19] [20]

a. Francis turbine

b. Pelton turbine and,
c. Kaplan turbine

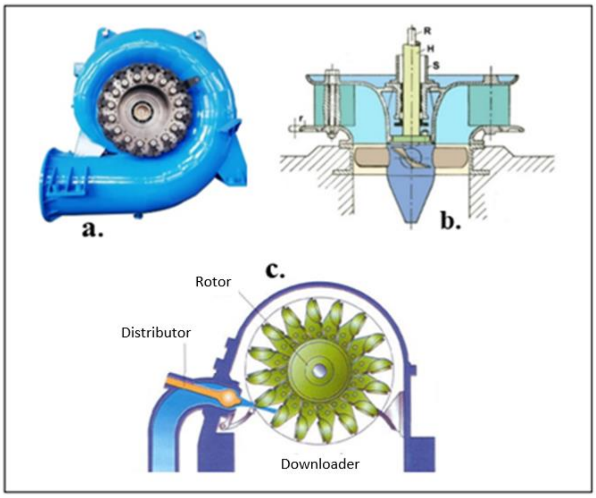


Fig. 3 Main types of turbines [8].

Another important consideration regarding the turbines is their characteristics, which will feed the algorithm. These characteristics are defined depending on the class or type of turbine. In general, the type of impeller, the specific speed (Ns), the water flow (Q), the max. height is considered. (Hmax), the efficiency (η) and the power (P) that said turbine will deliver. Table I shows the characteristics of the most used turbines [21].

TABLE 1
PARÁMETERS OF HIDRAULIC TURBINES

Turbines clases	Abbreviation designation	Impeller type	Ns (rpm)	Q (m3/seg)	H_{max} adm. (m)	η %	P (KW)
PELTON	TP1CH	1 Ch	10 – 30	0.03 – 0.41	90 – 300	***70-91***	30 – 900
	TP2CH	2 Ch	30 – 50	0.07 – 1.1	60 – 300		30 - 2500
	TP4CH	4 Ch	30 – 50	0.65 – 2.0	150 - 300		750 - 4000
MICHELL	TMB		40 – 160	0.12 – 1.0	12 – 80	***65-82***	30 - 150
FRANCIS	TFL	Slow	60 - 125	1.3 – 7	50 – 180	***80-92***	1500 - 4000
	TFN	Normal	125 – 225	0.25 – 2.5	20 – 150		150 - 750
	TFR	Quick	225 – 350	0.6 – 12	10 - 55		30 - 4000
	TFER	Extra fast	350 - 450	0.7 – 3.0	5 - 9		30 - 180
Kaplan and propeller	TK	Kaplan	300 – 600	5 – 25	8,5 – 35	***80-93***	400 - 4000
	TDH	propeller	500 – 1000	1.4 - 11	2,5 – 10		30 – 400

Note: [21]

In Peru, the production of national electrical energy in August 2023, including the Isolated Systems and the National Interconnected Electrical System (SEIN), was 5,189 Gigawatts/Hour (GWh), in that sense, the units that used the water, produced 1,745 GWh, which is equivalent to 15% of the electricity demand. The demand of the National Interconnected Electric System (SEIN) during the period 2006 - 2023 will grow at an average rate of 7.8 percent annually, which is why it is required to install 4,275 Megawatts (MW), of which 2,640 correspond to natural gas thermoelectric plants and 1,745 to hydraulic plants [22] [23]. These studies support our research regarding the need to have programs to efficiently size hydraulic turbines using ANN.

On the other hand, the research used NeuroShell 2, which combines powerful neural network architectures, a Microsoft® Windows icon-based user interface, sophisticated utilities and popular options to provide users with the best neural network experimental environment, Fig. 4. It is recommended only for academic users or those users who are concerned with classical neural network paradigms such as backpropagation. Users interested in solving real problems should consider NeuroShell Predictor, NeuroShell Classifier, or NeuroShell Trader [4].

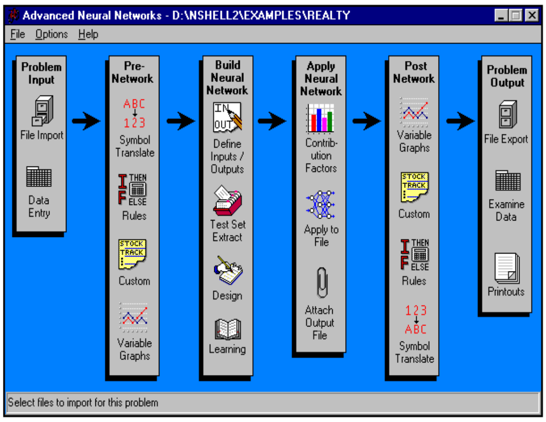


Fig. 4. NeuroShell 2 modules for an RNA application [4].

NeuroShell 2 automatically generates/compiles a DLL, which can be used in any programming environment, such as: Visual Basic, Access, Visual C++ and Java. [24]

III. METHODOLOGY

The research, given the great variety of hydraulic turbines that exists for a head and a given flow of water, proposes two methods to improve the selection and calculation of the parameters of a turbine without the need for an expert and in order to compare the results obtained and validate the solutions, the following applies:
a. The analytical or traditional method,
b. The neural network method

The two methods consider the following development:
The first phase involves classifying the different turbines by head, flow, specific speed, power and efficiencies; This classification is shown in Table II.

TABLE II
CLASSIFICATIÓN OF HIDRÁULIC TURBINES

Turbine Type	ns	nq	Hmáx adm.
Pelton 1 CH	10 a 13	3 a 4	1800 a 1300 m
Pelton 2 CH	12 a 20	4 a 6	1300 a 550 m
Pelton 4 CH	20 a 30	6 a 9	550 a 300 m
Francis slow	60 a 125	18 a 38	350 a 150 m
Francis normal	125 a 175	38 a 53	150 a 120 m
	175 a 225	53 a 68	120 a 80 m
Francis fast	225 a 350	68 a 105	80 a 35 m
	350 a 450	105 a 135	35 a 20 m
Kaplan	300 a 600	105 a 180	35 a 18 m
Tubular	300 a 800	180 a 240	18 a 12 m
Propeller	500 a 1000	240 a 300	12 a 5 m

Using the data in Table II, predictions were carried out for flow rates ranging between 0.03 m³/sec. and 20 m³/sec., as well as heights ranging from 3 meters to 300 meters. These predictions were made with the purpose of selecting and calculating the main dimensions of various hydraulic turbines that are located within these ranges.

Conceptualization of the Model - The design of an artificial neural network is proposed, considering:

a. Analytical method: The shape and dimension equations of Bovet and Lugaresi for hydraulic machines were used [24].

Turbine power (Kw):

$$P_{kw} = \frac{1000xQxHxnT}{1.340x75} \qquad (1)$$

Where:

P=Power in HP
Q= flow rate (m3/sec)
H=Jump height /(net jump in (m))
nt=Performance
1000= Number of liters of water in a m3

Specific number of power revolutions

$$N_s = \frac{n\sqrt{\frac{P}{i}}}{H.\sqrt[4]{H}} \qquad (2)$$

Where:

Nt=Specific speed in rpm
n=Specific speed in rpm
P=power in HP
H=Jump height in m
i= Number of nozzles

Net head - Single injector turbine (Hn)

$$H_n = \frac{C_o^2}{2g} + \frac{p_o}{\gamma} + z_o - z_a \qquad (3)$$

Jet diameter (*dch*)

$$d_{ch} = 550\sqrt{\frac{Q}{i\sqrt{H}}} \qquad (4)$$

Where: Dch=Jet gauge in mm
Q=flow rate (m3/sec)
H=Jump height in m
i= Number of nozzles

Turbine power (Kw):

The knowledge base covers the collection of data from real projects for each Hydro Turbine reported in tables.

Table III shows as an example the parameters for selecting the Pelton Turbine.

b. Neural network method: the commercial software NeuroShell 2 for Windows, the Backpropagation neural network, was used to predict the turbine variable (runner selections and dimensions); where there is an input layer with "x" neurons and an output layer with "y" neurons and at least one hidden layer of "z" internal neurons, which allows the execution of actions that optimize by making good predictions in the selection and design of hydraulic turbines [24].

TABLE III
SELECTING A PELTON TURBINE

H (m)	Q (m3/seg)	Rotation speed (rpm)	Turbine efficiency Pelton	Output coefficient P:(j)	Pelton power (Hp)	Pelton power (KW)	Ns Pelton (1Ch)	Vel. Sal. Pelton (m/seg.)	Pelton 1Ch
300	0.05	1200	70	0,97	138.158	100.184	11.3	37.19	10
300	0.2	720	70	0,97	552.632	400.736	13.56	37.19	10
200	0.04	1200	70,00	0,97	73.684	53.432	13.7	30.366	10
200	0.1	720	70,00	0,97	184.211	133.579	12.99	30.366	10
150	0.04	900	70,00	0,97	55.263	40.074	12.75	26.298	10
150	0.15	450	70,00	0,97	207.237	150.276	12.34	26.298	10
100	0.06	600	70,00	0,97	55.263	40.074	14.1	21.472	10
100	0.08	450	70,00	0,97	73.684	53.432	12.22	21,472	10
90	0.06	514	70	0.97	49.737	36.066	13.08	20.37	10

The data obtained on power and speed were tabulated in a spreadsheet in Excel format, the values found were transferred to the Datagrid of NeuroShell 2; which is the data entry mechanism; as shown in Table IV and V, highlighting the Pelton data.

TABLE IV
TABULATIÓN OF DATA IN EXCEL (POWER)

I2 | =(10*A2*B2*D2)/76

	A	B	C	D	E	F	G	H	I	J	K
1	H_m	Q_m3_seg	Vel_Rot.n_rpm	Ef_Pelton	Ef_Francis	Ef_kaplan	Ef_Helice	Ef_Michell	P_Pelton_hp	P_Pelton_kW	P_Francis
2	300	0,05	900	70,00	80,00	90,00	85,00	65,00	138,158	100,184	157,
3	300	0,05	1200	70,00	80,00	90,00	85,00	65,00	138,158	100,184	157,
4	300	0,05	1800	70,00	80,00	90,00	85,00	65,00	138,158	100,184	157,
5	300	0,07	720	70,00	80,00	90,00	85,00	65,00	193,421	140,258	221,
6	300	0,07	1200	70,00	80,00	90,00	85,00	65,00	193,421	140,258	221,
7	300	0,07	1800	70,00	80,00	90,00	85,00	65,00	193,421	140,258	221,
8	300	0,1	720	70,00	80,00	90,00	85,00	65,00	276,316	200,368	315,
9	300	0,1	900	70,00	80,00	90,00	85,00	65,00	276,316	200,368	315,
10	300	0,1	1200	70,00	80,00	90,00	85,00	65,00	276,316	200,368	315,
11	300	0,2	514	70,00	80,00	90,00	85,00	65,00	552,632	400,736	631,
12	300	0,2	600	70,00	80,00	90,00	85,00	65,00	552,632	400,736	631,
13	300	0,2	720	70,00	80,00	90,00	85,00	65,00	552,632	400,736	631,
14	300	0,2	900	70,00	80,00	90,00	85,00	65,00	552,632	400,736	631,
15	300	0,2	1200	70,00	80,00	90,00	85,00	65,00	552,632	400,736	631,
16	300	0,2	1800	70,00	80,00	90,00	85,00	65,00	552,632	400,736	631,
17	300	0,4	360	70,00	80,00	90,00	85,00	65,00	1105,263	801,473	1.263,

SelTurb

TABLE V
TABULATIÓN OFF DATA IN EXCEL (SPEED)

S2 | =(C2*POTENCIA(I2;1/2))/(POTENCIA(A2;5/4))

	A	B	C	D	E	F	G	H	I	S	T
1	H_m	Q_m3_seg	Vel_Rot.n_rpm	Ef_Pelton	Ef_Francis	Ef_kaplan	Ef_Helice	Ef_Michell	P_Pelton_hp	Ns_Pelton_1Ch	Ns_Pelto
2	300	0,05	900	70,00	80,00	90,00	85,00	65,00	138,158	8,47	5,9
3	300	0,05	1200	70,00	80,00	90,00	85,00	65,00	138,158	11,30	7,9
4	300	0,05	1800	70,00	80,00	90,00	85,00	65,00	138,158	16,95	11,
5	300	0,07	720	70,00	80,00	90,00	85,00	65,00	193,421	8,02	5,6
6	300	0,07	1200	70,00	80,00	90,00	85,00	65,00	193,421	13,37	9,4
7	300	0,07	1800	70,00	80,00	90,00	85,00	65,00	193,421	20,05	14,1
8	300	0,1	720	70,00	80,00	90,00	85,00	65,00	276,316	9,59	6,7
9	300	0,1	900	70,00	80,00	90,00	85,00	65,00	276,316	11,98	8,4
10	300	0,1	1200	70,00	80,00	90,00	85,00	65,00	276,316	15,98	11,
11	300	0,2	514	70,00	80,00	90,00	85,00	65,00	552,632	9,68	6,8
12	300	0,2	600	70,00	80,00	90,00	85,00	65,00	552,632	11,30	7,9
13	300	0,2	720	70,00	80,00	90,00	85,00	65,00	552,632	13,56	9,5
14	300	0,2	900	70,00	80,00	90,00	85,00	65,00	552,632	16,95	11,
15	300	0,2	1200	70,00	80,00	90,00	85,00	65,00	552,632	22,59	15,
16	300	0,2	1800	70,00	80,00	90,00	85,00	65,00	552,632	33,89	23,
17	300	0,4	360	70,00	80,00	90,00	85,00	65,00	1105,263	9,59	6,7

SelTurb

Next step the DSC file was created, as shown in Fig. 5

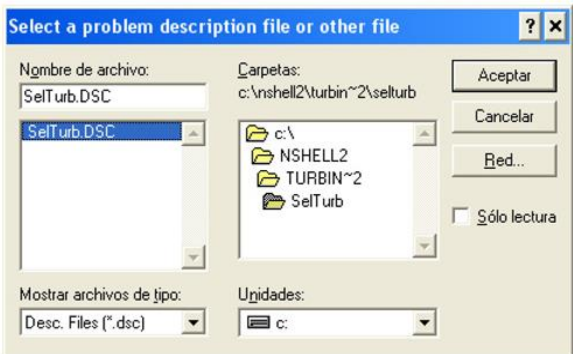


Fig. 5 Creating the DSC file in NeuroShell

Once the NeuroShell 2 files have been generated, the screen to enter the data is displayed, we select the inputs (input) and the outputs (output), as seen in Fig. 6.

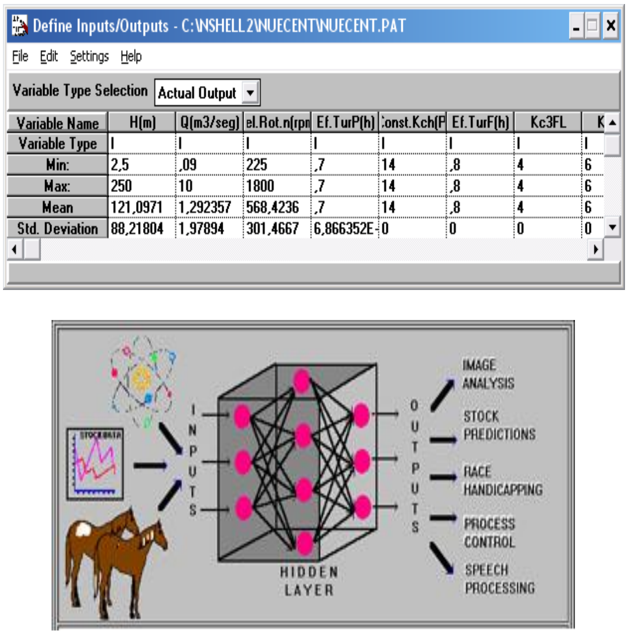


Fig. 6 Screen to select inputs and outputs

Once the data is entered, the learning rule is established based on the multilayer Backpropagation algorithm, the training algorithm performs its task of updating weights and gains based on the mean square error. The Backpropagation network works under supervised learning and, therefore, I need a training set that describes each output and its expected output value as follows:

$$\{p_1, t_1\}, \{p_2, t_2\}, \ldots\ldots, \{p_Q, t_Q\} \tag{5}$$

Where:

Pq=It is an entrance to the network

tq=Desired output for the qth pattern

To train the network that recognizes the turbine power, specific numbers and selection of the turbine type, the mathematical deduction of this procedure was carried out for a network with an input layer, a hidden layer and an output layer and then generalized for networks with more than one hidden layer [25]. The network is shown in Fig. 7.

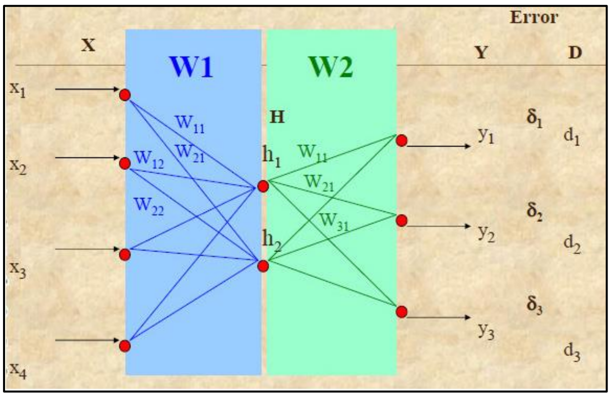


Fig. 7 Network training pattern

For training in NeuroShell 2, we interacted with the train menu and started training using 30 neurons, as shown in Fig. 8.

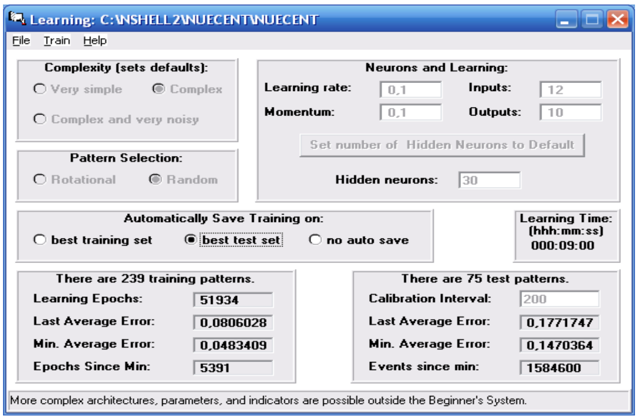
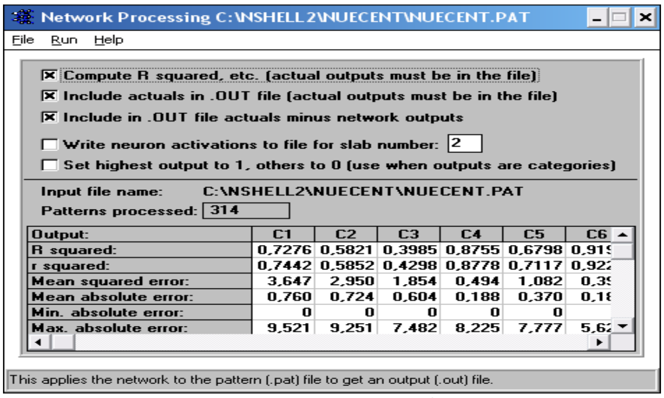


Fig. 8 Training after 10 minutes

After completing the training, the execution was tested by interacting with the "Run" menu, which resulted in obtaining the output of the process, as shown in Fig. 9.

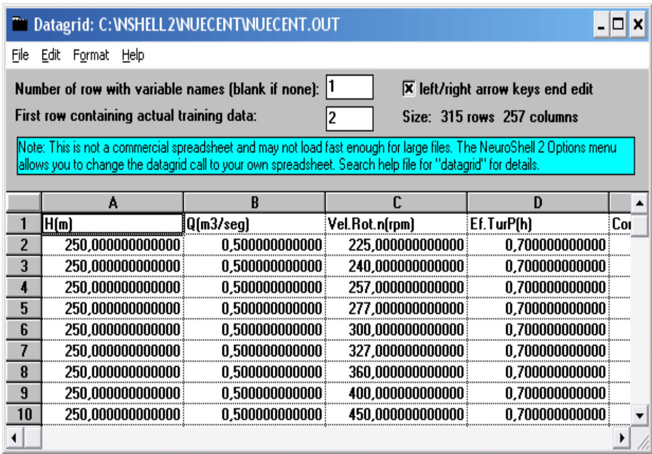


Output:	C1	C2	C3	C4	C5	C6
R squared:	0,7276	0,5821	0,3985	0,8755	0,6798	0,91
r squared:	0,7442	0,5852	0,4298	0,8778	0,7117	0,92
Mean squared error:	3,647	2,950	1,854	0,494	1,082	0,3
Mean absolute error:	0,760	0,724	0,604	0,188	0,370	0,1
Min. absolute error:	0	0	0	0	0	
Max. absolute error:	9,521	9,251	7,482	8,225	7,777	5,6

Fig. 9 Screen showing the output of the process

To export the files and facilitate their analysis and validation, the "Spreadsheet Export" function was used, the screen of which is displayed in Fig. 10.

Finally, the specialized functions Generate Runtime Systems and Datagrid were interacted with in order to examine the data files, shown in Fig. 10.



	A	B	C	D
1	H(m)	Q(m3/seg)	Vel.Rot.n(rpm)	Ef.TurP(h)
2	250,000000000000	0,500000000000	225,000000000000	0,700000000000
3	250,000000000000	0,500000000000	240,000000000000	0,700000000000
4	250,000000000000	0,500000000000	257,000000000000	0,700000000000
5	250,000000000000	0,500000000000	277,000000000000	0,700000000000
6	250,000000000000	0,500000000000	300,000000000000	0,700000000000
7	250,000000000000	0,500000000000	327,000000000000	0,700000000000
8	250,000000000000	0,500000000000	360,000000000000	0,700000000000
9	250,000000000000	0,500000000000	400,000000000000	0,700000000000
10	250,000000000000	0,500000000000	450,000000000000	0,700000000000

Fig. 10 Output files for validation

IV. Results

The results obtained were highly significant, resulting in this being an excellent predictive model, whose best performance was obtained towards the final phase of the training period.

In the data table that was provided to the network, there are values that meet the selection requirements, as well as others that do not meet these conditions; This was done to see if the network was capable of generalizing more and offering better results during the training process. Data from experts from several turbines was used, of which only those that met the established parameters are presented. At the end of the study, we have the following results:

Selection of a Pelton turbine: We enter the data of H = 120 m, Q = 0.15 m3/sec, with a normal rotation speed of 1800 rpm, the developed software (which we will call SD) selects (item202) and the main dimensions are calculated. of the Pelton 2ch turbine by method 1, 2, 3 and 4; Method 3 is shown in Fig. 11.

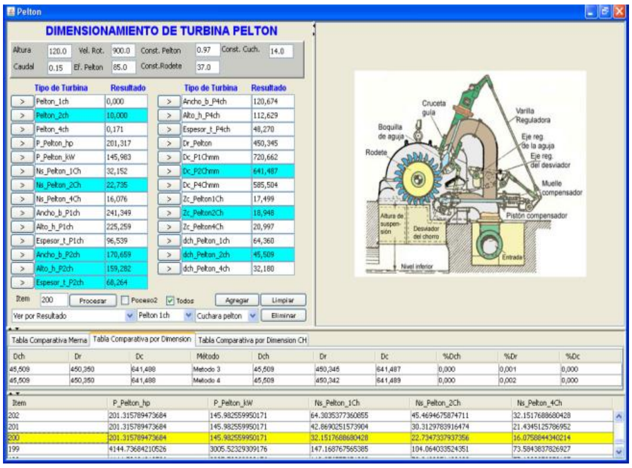


Fig. 11 Main dimensions of the
Pelton Turbine-Method 3

The comparison of the results according to the traditional method and the ANN method after training shows that in method 3, the values coincide exactly, validating the sizing using the ANN. The values are shown in Table VI.

TABLE VI
RESULT COMPARISON

Traditional Method			ANN method				[(Mt - SM)/Mt]*100 %		
			Method	Output variables					
P hp	P kw	Ns	SD	P (hp)	P (kw)	Ns	P (hp)	P (kw)	Ns
201.316	145.98	45.47	Method 1	201.32	145.983	45.469	0	0	0
201.316	145.98	45.47	Method 2	201.32	145.983	45.469	0	0	0
201.32	*145.98*	*22.74*	Method 3	*201.32*	*145.983*	*22.74*	*0.001*	*0*	*0*
201.316	145.98	22.74	Method 4	201.32	145.983	22.735	0	0	0

Selection of a Francis turbine: We enter the data of H = 100 m, Q = 2.5 m3/sec, with a normal rotation speed of 720 rpm, the developed software (SD) selects (item202) and calculates the main dimensions of the turbine Francis 2ch by method 1, 2, 3 and 4; Method 3 is shown in Fig. 12.

Selection of a Michell turbine: We enter the indicated data of H = 50 m, Q = 0.180 m3/sec, with a normal rotation speed of 900 rpm, the SD calculates the main dimensions of the Mitchell Turbine (SD) selects (item202) and the main dimensions of the turbine are calculated by method 1, 2, 3 and 4; Method 3 is shown in Fig. 13.

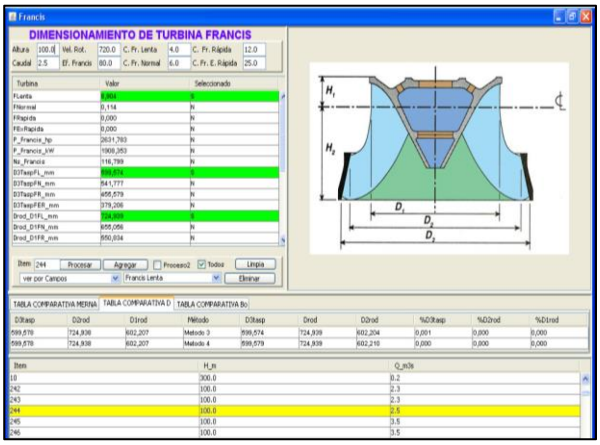


Fig. 12 Main dimensions of Francis Turbine-Method 3

The comparison of the results according to the traditional method and the ANN method after training shows that in method 3, the values coincide exactly, validating the sizing using the ANN. The values are shown in Table VII.

TABLE VII
RESULT COMPARISON

Traditional Method			ANN method				[(Mt - SM)/Mt]*100 %		
			Method	Output variables					
P hp	P kw	Ns	SD	P (hp)	P (kw)	Ns	P (hp)	P (kw)	Ns
2631.58	1908.3	116.8	Method 1	2630.4	1908.04	116.8	0.023	0.012	0
2631.58	1908.3	116.8	Method 2	2630.8	1907.96	116.78	0.031	0.016	0
2631.6	*1908.3*	*116.7*	Method 3	*2631.6*	*1908.28*	*116.7*	0.008	0.004	0
2631.58	1908.3	116.8	Method 4	2632.6	1908.51	116.8	0.039	0.013	0

Michell turbine:

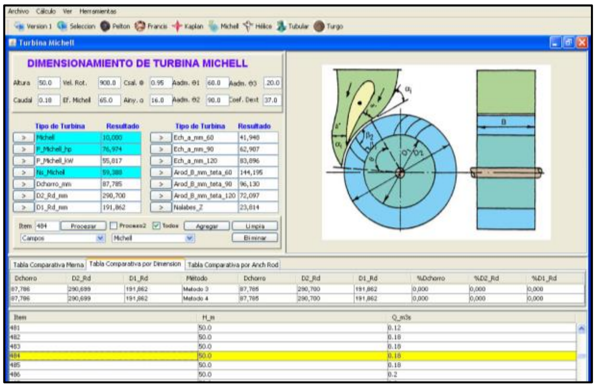


Fig. 13. Main dimensions of the Mitchell Turbine-Method 3

The comparison of the results according to the traditional method and the artificial neural network (ANN) method according to its training shows that in method 3 the values coincide exactly, validating the sizing using the ANN, shown in Table VIII.

TABLE VIII
COMPARACION DE RESULTADOS

Traditional Method			ANN method				[(Mt - SM)/Mt]*100 %		
			Method	Output variables					
P hp	P kw	Ns	SD	P (hp)	P (kw)	Ns	P (hp)	P (kw)	Ns
76.974	55.817	59.39	Method 1	76.974	55.817	59.338	0	0	0
76.974	55.817	59.39	Method 2	76.974	55.817	59.338	0	0	0
76.974	*55.817*	*59.39*	Method 3	*76.974*	*55.817*	*59.39*	0.008	0.004	0
76.974	55.817	59.39	Method 4	76.974	55.817	59.338	0	0	0

IV. CONCLUSIONS

The methods used in the research, both the traditional approach that uses analytical calculations to determine the main dimensions of the turbine, and the developed software that applies four methods for the selection and two methods for the calculation of the main dimensions of the turbine, lead to the following conclusions:

It is important to compile in files a sufficient number of real projects to feed the ANN with a reliable database (stored in Excel format), in this way the developed software makes adjusted estimates and provides real information about the selection and design of projects. hydraulic turbines for a mini hydroelectric plant, as explained by [4] and [20] who seek to optimize the calculation and design process of a Pelton turbine, in a minimum of time, without the user having to be compromised, both in the preparation of mathematical calculations; nor, in the production of plans concerning these turbines. In this regard, we agree with [16] who maintain that, to select the type of turbine, the turbine is first preselected in the flow and head nomograms provided by the manufacturers, and then the type of turbine is refined using the specific speed.

The training of the software developed in NeuroShell2 was carried out in the beginner system and in the advanced system, interacting with the tools. In the advanced system, the backpropagation network generates a C file that occupies 180kb, the GRNN network generates a C file that occupies 1.9 MB, these files cannot be compiled directly, so successive divisions of the source code are used, to obtain reliable results.

By entering the data of H (height), Q (flow) and Ve (velocity); The developed software selects the appropriate turbine that meets these parameters in order to generate the installed power of less than 10 MW. that the mini hydraulic power plant requires. When the output data is compared with the traditional method, equal values are obtained, which validates the proposed model. These results are shown in Figs. 11, 12 and 13 as well as the comparisons are shown in Tables VI, VII and VIII.

The Kaplan turbine failed to meet the stated requirements due to the paucity of available input data. Therefore, the results of the Michell turbine are presented, which during the simulation demonstrated output results that conform to the required standards.

The results obtained confirm that Artificial Neural Networks (ANN) are an invaluable tool in decision making when handling large volumes of information. Beyond the methodology used or the computing tool used to obtain the results, the approach through ANN has proven to be highly significant in this study. We corroborate our results with [6] who maintain that the results obtained allow us to confirm that the application of artificial intelligence based on the Neural Networks model contributes to decision making when it comes to investing large amounts of money.

The developed model emerges as a viable alternative for the generation of electrical energy from renewable sources, such as water. In this way, the deficiency of electrical energy in our country specifically in rural areas could be addressed and help mitigate the environmental impact.

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