RESUMEN DE TESIS DOCTORAL

Growth Evaluation of a Conifer Forest (*Pinus Cooperí* Blanco) using a Neural Net Backpropagation Trained with Distance Independent Competition Measures

Estimación del Crecimiento de un Bosque de Pino (Pinus Cooperí Blanco) por medio de una Red Neuronal Backpropagation Entrenada con Índices de Competencia Independientes de la Distancia

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Abstract
To make a decision about irregular forest handling practices is very difficult cause of some characteristics like age, natural life size diversity, and spatial distribution. A very important factor to fix growth forest is the competition about natural resources, so competition between trees should be considered to develop growth model. This is possible making use of parameters building with tree dimensions like diameter high, canopy extent, top high. These parameters are the distance independent competition measures. This research shows results product to use of backpropagation neural net trained with distance independent competition measures to forecast diameter and high growth. In this work we develop a growth model of a natural mixed forest of *Pinus Cooperí* Blanco, endemic specie of mountain region of Durango State, Mexico. This specie has been barely studied and is very important in wood exploitation production, because is used in timber wood production, and triplay fabrication.
Key Words: *Pinus Cooperí* Blanco, backpropagation neural net, independent distance competition measures.

Resumen
La toma de decisiones en el manejo de bosques irregulares se dificulta en gran medida por las características como: una alta complejidad por su diversidad de edad, tamaño y distribución espacial. Una forma de conceptuar el problema es visualizar el bosque como un ecosistema, donde su estudio se basa en las interrelaciones de los organismos y su medio ambiente. Un factor que determina el crecimiento de un bosque es la competencia que existe entre los individuos de la población por recursos, por lo que la competencia entre los individuos de un bosque debe ser considerada en el desarrollo del modelo de crecimiento. Esto se logra haciendo uso de parámetros basados en las dimensiones de los árboles; como son los índices de competencia independientes de la distancia. En esta investigación se muestran los resultados obtenidos de la utilización de una. de una red neuronal backpropagation, entrenada con índices de competencias independientes de la distancia en la predicción del crecimiento en diámetro y altura de un bosque de la especie de pino *Pinus Cooperi* Blanco, árbol poco estudiado, sin embargo de una gran importancia en su explotación por su aprovechamiento en la producción de madera y uso en la producción de hojas de triplay.
Palabras clave: *Pinus Cooperí* Blanco, red neuronal backpropagation, índices de competencia independientes de la distancia.

1 Introduction

An important element of forest handling is forecast future conditions of development. A forest can be defined like an ecosystem [31], formed for a woodland canopy, where trees are principal components and they have interrelations with others organisms (insects, fungus, fauna), environment and climate.

A forest is a biological system with a great complex degree in its behavior description [3]. Where natural complexity of a system arises from a lot number of parts of a system make an effort collective. It is often practically impossible to forecast in a detail manner single component behavior or of precise way behavior of all the system [30]. A system can be seen like a whole. Therefore it can show a behavior defined whole, and this behavior usually own important characteristics. May be its most important characteristic is robustness, where is not affected typically to cause of single fails or perturbations of component.

In this work we try to forecast diameter and high growth of pine where a tree is itself a complex system building for millions of cellules interacting between them and they are affected by extern factors. A Tree itself is part of a community called forest. The members of the system interact among them, with others organisms and environment. Thus, of this group of interactions between trees and its surroundings and interrelations between its own cellules part of tree. It should be extracting a characteristic behavior that obtains to detach rings growth of wood, which derives from wide and large growth of the trunk of tree to cause of activity of the cambium.

A system that is subject to complex (external) influences has a dynamics that may be modeled statistically [18]. The statistical treatment simplifies the complex unpredictable stochastic dynamics of a single system, to the simple predictable dynamics of an ensemble of systems subject to all possible influences [29]. A random growth tree is the prototype stochastic process. Over time, the random influence causes the ensemble of tree cells growth to spread in space and form a Gaussian distribution. When there is a bias in the random tree growth, growth tree have a constant velocity superimposed on the spreading of the distribution.

While the microscopic dynamics of physical systems is rapid and complex, the macroscopic behavior of many materials is simple, even static. The origin of simplicity is an averaging over the fast microscopic dynamics on the time scale of macroscopic observations (the ergodic theorem) and an averaging over microscopic spatial variations. The averaging can be performed theoretically using an ensemble representation of the physical system that assumes all microscopic states are [15]. Using this as an assumption, a statistical treatment of microscopic states describes the macroscopic equilibrium behavior of systems.

Growth can be considering a gradual change in time. This natural physiological process can be appreciate and represented by means of a curve, it is being a graphical representation of all stages of the life. When is studied growth, it can be seen like a system and it achieves to be represented by means of a model [4]

2 Background

Models based in statistical methods have been reported to forecast forest growth making use of distance independent or dependent competition measures ([2], [26] and [27]). To use artificial neural nets is a new approximation that results in a very promising tool in dynamic's study of forest growth [17].

Recently, interest in the use of artificial neural networks (ANN), known as Parallel Distributed Processing (PDP), has grown in various fields [25]. Neural networks constitute a class of statistical models, which can be applied in a broad range of applications, from exploratory data analysis and visualizations to classification and regression problems. In forest management current ANN applications include: (1) forest land mapping and classification, (2) forest growth and dynamics modeling (3) spatial data analysis and modeling (4) plant disease dynamics modeling, and (5) climate change research. In neural network forest growth and dynamics modeling, the goal is to build a model based on the observed data, which can represent the essential properties of the process under interest.

ANN has also begun to emerge as an alternative approach for modeling nonlinear and complex phenomena in forest science ([1], [6], [20], and [17]). The potential predictive capability of ANN, based on some supervised learning and training, can provide optimal solutions to forest resource management problems.

Development of handling practices to pine forests is similar around the world. Therefore, a few forest theories could be generalized to the same tree location and allow describing a future develop of the forest ecosystems; because meteorology conditions, soils quality and forest weed species could be very different. In these cases are necessary to recognize dynamics of growth in every location and their effects product of interrelations soil-climate-vegetation in forest location growing. The characteristic forest in Mexico country and mountain region at Durango State is irregular forest. This kind of forest is composed of individual with very different size and aged or/and very different spatial distribution of the location. In this very complex forest, to know production wood at the present and future time is very difficult to cause of heterogeneity of the individuals and soil. Therefore is necessary more information about forest locations and approach to modeling the dynamics of complex systems.

In this work research back propagation neural net performance training with distance independent competition measures forecasting diameter, height growth at conifer specie *Pinus Cooperí* Blanco irregular forest location.
We model growth conifer trees making use of distance independent competition measures. These measures treat to explain variation in the height and diameter growth of individual conifer trees. This competition is based on the ratios of competing individual tree dimensions (diameter, height) with the neighborhood dimensions.

Forest growth models that describe forest dynamics (i.e., regeneration, growth, succession, mortality, and survival) have been widely used in forest management to update inventory, predict future forest yield, and assess species composition and ecosystem structure and function under changing environmental conditions. Despite advancements in developing stand, and individual tree growth models, tree mortality components have been simplified (using random probability), yielding growth and yield models with large variability and major projection bias in their predictions [5]. Much progress has been made in this area since the initial use of ANN to model individual–tree mortality in 1991 [8]. In the same year, Guan and Gertner [9] successfully developed a model, based on an ANN, which predicts red pine (Pinus resinosa Ait.) tree survival. They found that the ANN-based red pine survival model not only fit the data better than a statistical model, but also performed better on future data. The model was also flexible enough to model both small and large, and slow growing red pine trees. Their approach was further enhanced by integrating a proper training algorithm and computational platform to model individual tree survival probability by Guan and Gertner [10]. On other hand, Hasenauer and Merkl [12] demonstrated an application of unsupervised neural networks for predicting individual tree mortality within growth and yield models in Austria. They found that the neural networks performed slightly better than a conventional statistical mortality model based on the LOGIT approach. Recently, Guan [11] proposed a framework for assessing the prediction quality of process-based mechanistic forest growth models. The method involucres four steps: (1) assuming distributions for parameter values, (2) screening parameters, (3) outlining model behavior through sampling, and (4) approximating model behavior based on the sampled points. This proposed method was then applied to a carbon-balance based forest growth model developed by Valentine [28], and has been demonstrated to effectively analyzing large and complex models.

3 Metodology and Materials

The study was realized with information obtained of the experimental location Cielito Azul, that is situated in property the “Veredas”, lote 4, in zone assigned to Unidad de Conservación y Desarrollo Forestal 4, en el municipio de San Dimas, Estado de Durango, geographic located among 24 22’ and 24 23’north and 105 53’ and 105 54’ west, with a high average of 2700 meters. Topography is from wavy to flat, with a slope average of 15%.

Substrate is characterized by to be formed with a mix of cambisol eutric, prevailing land of lime-clay and lime-sand with a PH of 5.0 and a thickness of the stratum of organic matter of 5 centimeters. Climate present characteristics from temperate semi cold sub humid, with summer rainy and a winter precipitation greater than 10.2 millimeters.

The mean annual precipitation on this location is of 800 millimeters. Mixed conifer forest type includes Pinus and Quercus genus with principal population of *Pinus Cooperí* Blanco and Pinus Durangensis Martinez. Several bush vegetation genus and wild plants genus.

Forest population includes pines which are growing into same time period with similar ages and others pines with different ages This population has a distribution diameter size between 5 and 80 centimeters.

Basal area average fluctuates among 12 and 23 cubic meters per hectare. Thirty six permanent experimental locations (SIPS sitios permanentes de investigación sílvicola) were established between years 1966 and 1968. Five treatment of were applied and one witness. Size measurement has been done from years 1972, 1979, 1982, 1986, 1993 and 2004. Each location is divided in four square areas from 25 X 25 meters [19]. In each square area was established a source point in their vertexes. Distances in two axes (X,Y) was measured from square area vertexes for each one tree and they were located spatially .

Each tree was taken measures: specie, type, normal diameter, bark thickness, hurt condition, total height, height from clean shaft, class or predominant features, vitality, dynamic tendency, and canopy projection. Measurements inside a five years period, from years 1982 to 1986 was utilized for the distance independent competition measures building and network training and results validation.

3.1 Distance independent competition measures

Distance independent competition measures are parameters which treating to describe a relation between size dimensions and population competency by resources like sun light, soil nutrients, and water. In this research twelve distance independent competition measures are utilized to train the neural net backpropagation.

Eleven distance independent competition measures were parameters built by Valles [27] especially for the *Pinus Cooperí* Blanco, another one is Glover and Hool [7] parameter that has been utilized to predict species growth from USA West Mountains.

Mexican mountains were *Pinus Cooperí* Blanco grow, could be considered continuation from Pacific USA Cost Mountains.

Network was trained with twelve distance independent competition measures (Table 1) and nine parameters like pine age, diameter, height, canopy height, canopy amplitude, basal area, another more.

Table 1. Distance independent competition measures

$$IAB = \frac{\left\lfloor (\sum (\pi (D_j / 2)^2)) / n \right\rfloor}{(\pi (Di / 2)^2)}$$

(1) Glover and Hool measure.

$$IABD = \frac{\left\lfloor (\sum (\pi (D_j / 2)^2)) / n \right\rfloor}{(\pi (D_i / 2)^2)} (na / ha)$$

(2) Basal area by density measure.

$$IAM = \frac{\left\lfloor \sum (AT_j) / n \right\rfloor}{(AT_i)}$$

(3) Mean height measure.

$$IAMD = \frac{\left\lfloor \sum (AT_j) / n \right\rfloor}{(AT_i)} (na / ha)$$

(4) Mean height by density measure.

$$IDC = \frac{\left[\sqrt{\left[(\sum D_J{}^2) \right]} / n \right]}{(D_i / 100)}$$

(5) Quadratic diameter measure.

$$IDCD = \frac{\left[\sqrt{\left[(\sum D_J{}^2) \right]} / n \right]}{(D_i / 100)} (na / ha)$$

(6) Quadratic diameter by density measure.

$$ILC = \frac{\left\lfloor (\sum (AT_j - AF_j)) / n \right\rfloor}{(AT_i - AF_i)}$$

(7) Canopy height measure.

$$ILCD = \frac{\left\lfloor (\sum (AT_j - AF_j)) / n \right\rfloor}{(AT_i - AF_i)} (na / ha)$$

(8) Canopy height by density measure.

$$IAC = \frac{\left\lfloor (\sum Rcn_j + Rcs_j + Rce_j + Rco_j)/4 \right\rfloor / n}{(Rcn_i + Rcs_i + Rce_i + Rco_i)/4}$$

(9) Canopy amplitude measure.

$$IABT = \frac{\left\lfloor \sum(\pi((D_j/2)^2)) \right\rfloor}{(\pi(Di/2)^2)}$$

(10) Basal area total measure.

$$IACD = \frac{\left\lfloor (\sum Rcn_j + Rcs_j + Rce_j + Rco_j)/4 \right\rfloor / n}{(Rcn_i + Rcs_i + Rce_i + Rco_i)/4}(na/ha)$$

(11) Canopy amplitude by density measure.

$$ISP\,2 = \beta_1 \left[1 - \exp\left(-\beta_2 * eb\right)\right]^{\beta_3}$$

$$\beta_3 = \ln\left(hd / \beta_1\right) / \ln\left(1 - \exp\left(\beta_2 * edad\right)\right)$$

(12) Richness Place measure (Polimorfic2, Chapman-Richards, [32]).

AT = Total tree height.
D_j Competitor trees.
AF =Clean trunk Height.
π = (3.1416).
Isp2 = Richness soil parameter.
n = tree number inside a plot.
eb = Aged reference.
na/ha = tree number per hectare.
hd = Predominant height.
LC_i = Canopy long live.
β_1, β_2 = Model parameters.
Rcn, Rcs, Rce, Rco, = Canopy radius, north, south, east, and west.

4 Solution Strategy

The process of statistical data analysis was divided in three stages. The first stage involved collecting the data set. It included selecting the variables to be measured, normalizing the data, selecting the features, and taking care of outliers and missing values. In the second stage the model was built using the data. Model family, training algorithm and optimizing criteria were selected according to the objectives of the analysis. In the third stage, results from the model were analyzed, and the model and features used were reviewed. When the model performed adequately, it was implemented for its planned purpose.

4.1 Data Collection

Statistical analysis begun with data recollection; this step was realized taking size measures of each tree: diameter, canopy amplitude, canopy high. And with these dimensions were built the distance independent competition measures, parameters utilized to the training the neural net backpropagation.

It was looking with these parameters describe in detail form behavior system. In this work parameters were chosen making use of priori knowledge. Forest experts from years have been use competition measures to predict forest.

Thus it was modeled growth conifer trees with distance independent competition measures. These measures treat to explain variation in the height and diameter growth of individual conifer trees. This competition is based on the ratios of competing individual dimensions easy to get like: diameter, height, canopy amplitude with the neighborhood dimensions.

4.2 Preprocessing Data

In this step was involved the manipulating of information into an initialization of weights and bias range where adequate neural net performance could be achieved. It was analyzed between two options: a) rescaling dates to make all the elements lie between 0 and 1, b) standardizing all dates, where the mean is first subtracted and the result divided by the standard deviation, thereby obtaining a standard normal random variable with mean 0 and standard deviation 1.

With the intention of chose among the two options several neural nets were trained to predict diameter growth and it was obtained less training time with standard normal random variable with mean 0 and standard deviation 1.

4.3 Neural net morphology

Multilayer perceptrons with one single hidden layer with logistic activation function is reported in literature [14], [16] like universal approximators. That is, they are capable of arbitrarily approximation of essentially arbitrary mappings from the $[-1, +1]^n$ hypercube to the (-1, 1) interval.

4.3.1 Selecting activation functions

Taking how criterion to look for a faster training net among logistic sigmoid and tangential sigmoid activation function. It was used tangential function because results showed that was lesser consuming time option.

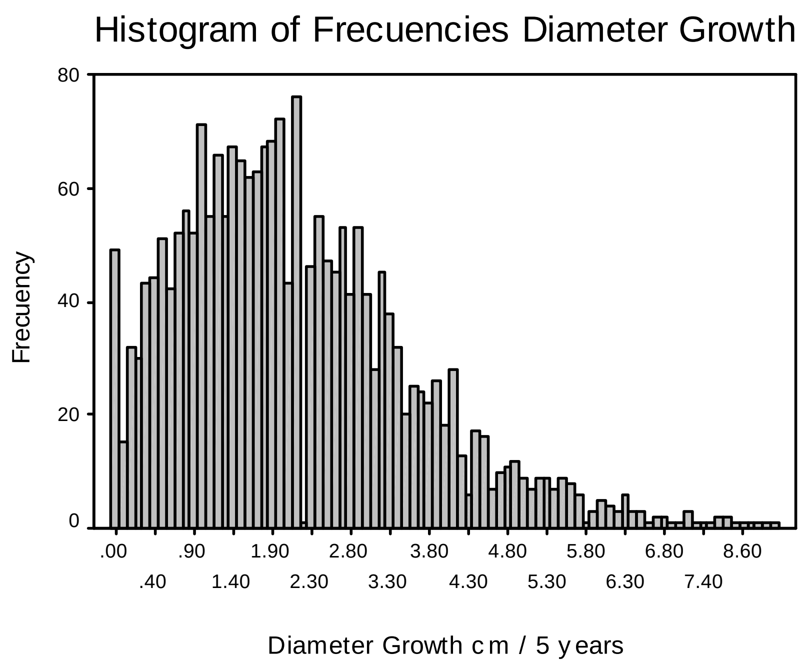

Fig. 1. Frequency histogram of diameter growth in a *Pinus Coopertí* Blanco forest

4.3.2 Optimization method

Neural net weights and bias must be adjusted to approximate a function system behavior. Making use from an optimization algorithm the variation in weights and bias can be optimized. Large size dimension neural net makes only possible to use a optimization algorithms with does not present memory computer problems, thus conjugate gradient [21] and "RPROP" backpropagation resilent [23], are methods recommended in large size neural nets. Considering neural net training consuming time was selected conjugate gradient algorithm; it was utilized conjugate gradient because was faster to converge to the error medium quadratic than RPROP method.

4.3.3 Network architecture

Next step was looking for network capable to learn all system complexities presented into training set and if it was able to forecast diameter and height growth of *Pinus Cooperí* Blanco. Random initialization was made in weights and bias.

Looking for good neural net generalization were used 21 inputs, all information problem, in order to can treat with the high system complexity and to obtain advantage over statistical methods who are limited to make use not much parameters because if increase its number appear an increase of interrelation between them and the model produced can not be supported by its basic principles. And it was of interest to observe the network treats with redundancy between parameters.

Thus, first architectures were simple and small and was increase size, first in number of neurons by layer and then in number of layers, until to get a good generalization.

Thus, it could be concluding to increase layers number of neural net improve rate learning capacity training patterns.

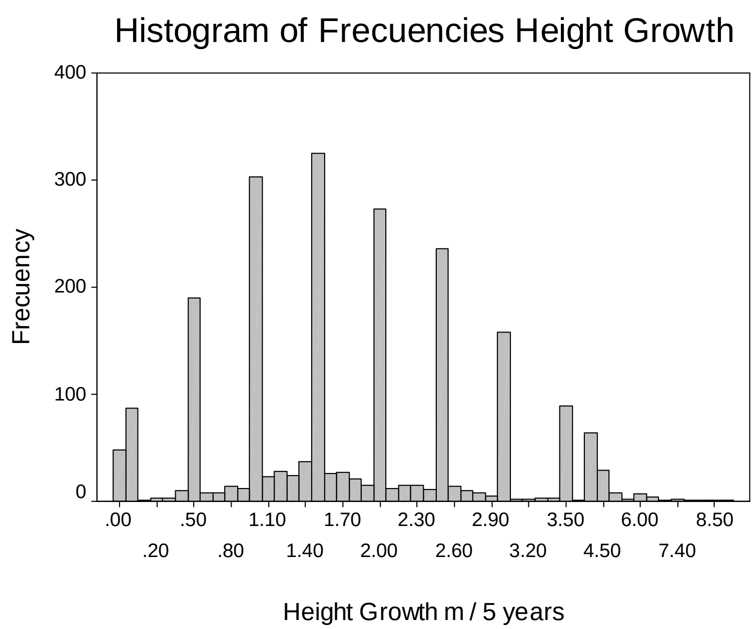

Fig. 2. Frequency histogram of height growth in a *Pinus Cooperí* Blanco forest

4.4 Network training

The better capacity generalization of the neural net was found stopping training in different errors quadratic medium: 0.1, 0.01, 0.001, 0.0001, 0.00001. This was made with intention to observe generalization evolution.

4.5 Validation sample selection

The validation sample seeks to show system behavior and this was made seen pattern behavior of the relation between distance independent competition measures, size tree dimension, tree aged, richness location nutrients and water with diameter and height growth rate. From diameter and height growth of a mixed forest with *Pinus Cooperí* Blanco (figure 1 and 2) it was selected a validation sample with a population of 21 trees to forecast diameter growth (Table 1); this sample has a diameter growth range among 0.6 to 3.8 centimeters per 5 years (Table 2). And It was selected a sample of 30 trees to forecast height growth between rate of growth of 0.5 to 3.5 meters per 5 years (Table 3).

4.6 Size sample determination.
To accept size sample has to be into a confidence interval. That was determined by Montgomery's [22] procedure (equations 13, 14, and 15):

$$\sigma = \frac{\sqrt{\sum (E-e)^2}}{(n-1)} \tag{13}$$

$$E = \sum e \tag{14}$$

$$n = \frac{N * Z^2 * \sigma^2}{\Delta^2 * (N-1) + Z^2 * \xi} \tag{15}$$

N= population size.
n= sample size.
ξ = Parameter with a value 1.0
e= difference between validation and predicted observation.
Z= Values 0.95, 1.96, 3.0 for confidence interval 90, 95 and 100%.
Δ = error type I of 0.1, 0.05, 0 for a confidence interval of 90, 95 and 100%.

Table 2. Diameter Growth (Validation sample)

Sample frequency	Diameter growth rate cm/5años	Population frequency
2	0.6	41
1	0.7	51
1	0.9	51
2	1.0	70
1	1.1	54
1	1.2	65
1	1.3	54
1	1.5	64
1	1.6	61
1	1.7	62
1	1.9	67
1	2.1	42
1	2.2	75
1	2.5	46
1	2.7	52
1	3.1	27
1	3.2	44
1	3.4	31
1	3.8	21

Table 3. Height growth (Validation sample)

Frequency sample	Height growth rate m/5años	Population frecuency
1	0.5	190
8	1.0	302
6	1.5	324
1	1.6	25
1	1.8	20
2	2.0	272
5	2.5	235
1	2.6	13
3	3.0	157
2	3.5	88

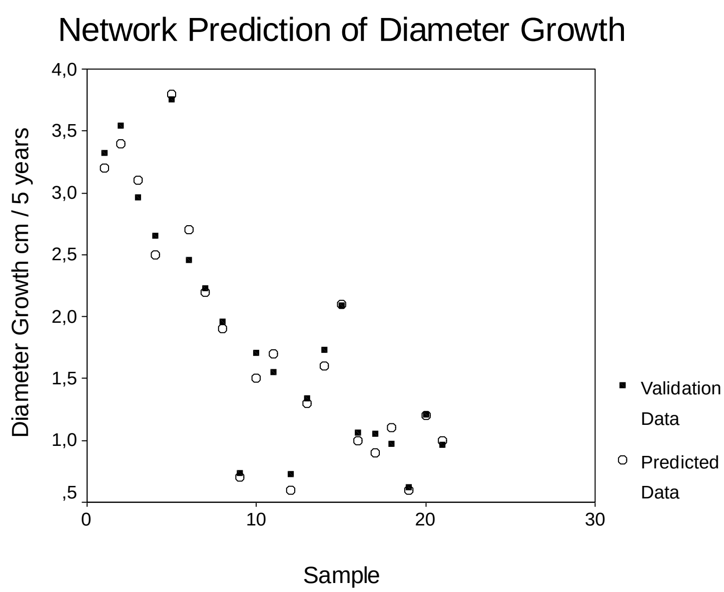

Fig. 3. Prediction of diameter growth

5 Neural Net Results

5.1 Diameter growth forecast

Several sizes of nets were utilized and were stopped in different errors quadratic medium: 0.1, 0.01, 0.001, 0.0001, 0.00001, seeking a good net generalization and this was found in a neural net with 21 inputs and 1 Output where data were standardized with mean 0 and standard deviation 1.

Morphology: Neural net backpropagation, with 6 layers, 5 hidden layer, 30 neurons, with tangential activation function, 1 output layer lineal activation function, Conjugate gradient optimization algorithm. Network was trained 2138 epochs, until achieved an error quadratic medium of 0.01

Pattern behavior presented in validation sample was predicted by trained neural net with 90% approximation into confidence interval of 90% (figure 3).

5.2. Height growth forecast

Several sizes of nets were utilized and were stopped in different errors quadratic medium: 0.1, 0.01, 0.001, 0.0001, 0.00001, seeking a good net generalization and this was found with a 21 inputs 1,Output network, where training pattern was standardized mean 0 and standard deviation 1.

Morphology: 6 layers, 5 hidden layer with 30 neurons, with tangential activation function and 1 output layer with lineal activation function. It was used conjugate gradient optimization algorithm. Network was trained 1023 epochs, until achieved an error quadratic medium of 0.1.

Pattern behavior presented in validation sample was predicted by trained neural net with 95.5% approximation into confidence interval of 90% (figure 4).

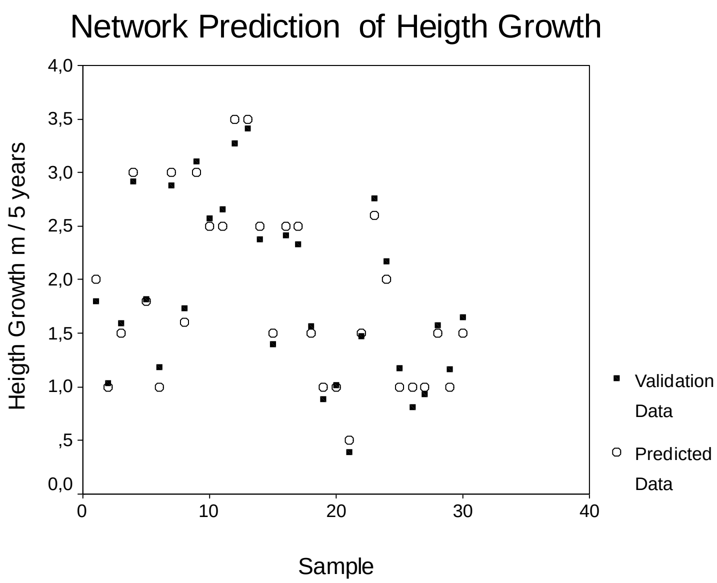

Fig. 4. Prediction of height growth

6 Analysis of Results

With a neural net back propagation trained with distance independent competition measures is capable to forecast diameter and height growth from a natural mixed forest with *Pinus Cooperí* Blanco. With only 2191 dates was possibility forecast diameter growth in a sample of 21 dates with 90% of exactitude in confidence interval of 90% and to forecast height growth of this very complex biological system with 95.5% of approximation in a confidence interval of 90%. Thus, we can conclude taken these results like base, neural net Backpropagation is an adequate tool to approximate this complex biological system.

It was necessary to make use of all parameters in order of to describe most quantity of system characteristics; however network had to be able to treat with redundancy between some parameters.

Neural nets which were capable to generalize diameter and height growth presenting how common characteristic that the training was stopped when error quadratic medium achieved was not small 0.01 in diameter growth and 0.1 in height growth. Neural nets have not learned the training pattern with much precision but were capable to forecast with a very high exactitude. This can be explained by the complexity system characteristics. Thus is necessary a lot abundance of information to describe with more exactitude every tree growth stage in this very complex system where each tree is surrounded by different trees groups in aged, in height, in soil spatial distribution.

It was seen that necessary information to describe this problem in very acute manner can grows exponential shape if it is considered to include others parameters produced for biological and physical systems that have influence over forest growth. Moreover it can be obtained excellent results if there are enough growth information of different ranges of growing; making use only of distance independent competition measures, like parameters to train neural nets this in base of results obtained in this work.

7 Conclusions, Recommendations and Future Work

7.1 Conclusions

- A neural net trained with distance independent competition measures is an adequate tool to forecast diameter a height growth of *Pinus Cooperí* Blanco forest.
- Positive results from neural net backpropagation use in this research show how this tool was capable to forecast behavior of a very complex system.
- Neural net back propagation result in an efficient memory computer capacity use and makes possible to resolve problem of estimating forest growth in the same place of timber exploitation.
- Neural net back propagation was able to treat with redundancy between parameters.

7.2 Recommendations

- Exist possibility of model others biological complex systems by results observed in this work using backpropagation neural net capacity for modeling a complex system, how is a growth forest.
- Utilization of independent distance competence measures produce dynamic model of static parameters. Tree life is long than human life so time to obtain information about growth tree is difficult. Thus, is recommendable makes use of this kind of parameters to express the behavior of this biological system.

7.3 Future work

It will make utilization of a neuro fuzzy neural net to forecast growth forest of *Pinus Cooperí* Blanco.

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