Design of Intelligent Expert System with inference by micro- and nanoinstrumentation.

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Abstract- This work shows a technology of artificial cloning for industrial sensors by means of the use of neural networks and genetic mapping. The neural networks allow develop to the intelligent structure of the micro- nanosensors, for it, the method of activation of random values is used to train the sensors and to carry out the learning starting from real devices, the genetic mapping allows the generation of codes for the cloning procedure, for it the mutation processes, crossing, reproduction and investment are used also, an example of a cloned sensor that determines the index of viscosity of lubricant oils with phenol for a monitoring system is briefly explained. The present article shows the results of the research carried out in the project on the development of a real time monitoring technology for the content of phenols in industrial wastewater. In - line dump flows, treatment tanks, stabilization pools In the open water and in the discharge of the water spill as part of the challenge presented by ECOPETROL on the need for decontamination of the wastewater in the Barrancabermeja Oil Refinery where they include the results on the design, development and implementation of a methodology that Through the detection of contaminants in real time, uses a network of sensors based on micro-nanobioinstrumentation with electronic nose, artificial tongue and spectrophotometric eye, supported in mobile technology for the monitoring of parameters of water quality (phenol content) in lines of Pipe in vertimient and effluents, the article presents the results development of a real-time monitoring system and on-line control by mobile technology of water quality parameters (phenols) in pipeline line for shedding and effluents that emulate by functional replication of the senses of smell, taste and spectrophotometric vision by artificial cloning that is applied in the design of the sensor network and control systems.
Keywords: Artificial cloning, genetic mapping, sensors network micro nanobioinstrumentation.

I. INTRODUCTION

The technology of artificial cloning of industrial sensors, as presented here, consists of a group of means and procedures based on tools of artificial intelligence these are then applied in the reproduction of high fidelity of real devices used in automation and control of industrial processes. This is based on the integration of neural networks techniques and genetic algorithms. A method, a procedure and utilities form this technology. The method consists of the application and interpretation of the genetic mapping that it contains; the codes of the functional structure of the sensor. The mapping is a group of bars of codes that describe the functional operative units of the sensor, each operative unit is formed by unitary elements that represent a part of the operation of the sensor such as deviation of the angle of incidence, variation of the intensity of the sheaf of light, etc. A code is a series of digits that represent a part of the operation of the sensor where each digit represents a position inside the functional structure (see ***Fig. 1***). The procedure consists of the application of a group of guidelines directed to the structural connections of the neural networks which facilitates the flow of information for the learning of the cloned sensor. The utilities are criteria likeness that apply measured a dimensional and they include parametrical characteristics of the real devices to clone that allow a sensor to reach a cloned version.

Cloning Process.

Five stages compose the process of cloning artificial sensors.

Stage 1: in this stage the devices are selected to clone. The population is divided according to the number of objectives given in functional operative units; the group of operative units is called “objective function”. For example, for an I number of N devices that constitute the population and an I number of n operative units, the population is divided in an agreement population’s part with the units whose size is N/n. Then, you re-iterate with a genetic algorithm each subpopulation with a strongest different objective function with the purpose of selecting the individuals; that is, to assure that each objective function is evaluated. Then, priority is assigned (hierarchical classification) to the functions objective depending the problem be solved. Finally, each function is selected according to its priority and it is evaluated

Digital Object Identifier (DOI): http://dx.doi.org/10.18687/LACCEI2018.1.1.401
ISBN: 978-0-9993443-1-6
ISSN: 2414-6390

on each subpopulation. This is carried out until evaluation of all the functions objective. Is achieved to assure the diversity, the weakest individuals are replaced in each subpopulation.

Stage 2: Are obtained the partial solutions S1, S2, S3, and Sn for each operative unit. The union of these solutions will allow to conform a new global population, to randomly which is applied a objective function that has been selected. This process is repeated until a certain number of iterations (fixed as convergence criteria) to assure that each function objective was evaluated inside the total population with a high reliability.

Stage 3: in this stage, in each subpopulation one selects the individuals that have the minimum value of the objective function that is evaluated. The number of individuals that are selected (for each sub population) it is taken as information to define the coefficient that will ponder each one of the components of the multiple objectives function (the group of different operative units). Finally, the total population is generated as the union of all subpopulations and is evaluated using the multiple objectives function [3] considered according to certain previous values.

Stage 4: in this stage the objective function is selected to evaluate, among the operative units that compose. One should make sure that all the functions are evaluated a definited minimum number of times.

Stage 5: in this stage a process of optimization is carried out with values and spaces characteristic of the partial solutions obtained in the stage 3 using the multiple objectives function resulting in stage 4. Then, the number of individuals is determined that give a minimum solution; that is to say satisfying the coefficient of consideration of the functions objectives with regard to the multiple objectives function. This represents the cloned device. For this example, the real analyzer is replaced a cloned intelligent sensor [1] starting from the real device due to frequent flaws presented in the system.

II. MATERIALS AND EXPERIMENTS

Work Application

Let us consider, a plant of extraction for lubricant oils with phenol (see ***Figure 1***) and let us consider that this prepares, among other, of an analyzer (sensor of the refractory meter) on-line and the whole instrumentation associated to the monitoring of the process that are centralized in a team that serves as operation interface.

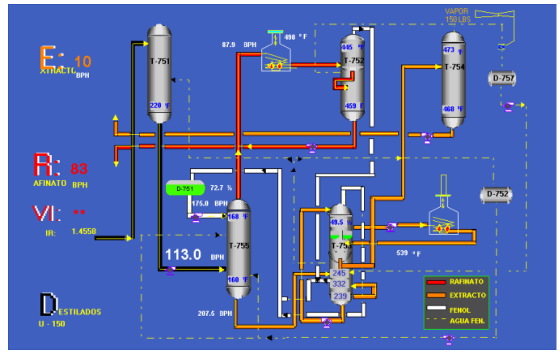

Fig. 1. *Plant for extraction of lubricant oils with phenol.*

The sensor determines the index of viscosity of lubricant oils with fenol. For this, it calculates the refraction index starting from a sheaf of monochrome light and then processes that information through a linear relationship with the index of viscosity. This information constitutes the primary element for later prosecution on the part of the monitoring system, which registers and permanently deploys the obtained information of the cloned sensor.

The analyzer (see ***Figure 2***) it determines the refraction index through the solution S that is refracted measuring the critical angle of refraction [8]. For it, the light coming from the light source L goes against the interface among a prism P and the solution. The rays of light meet with this surface to different angles. The reflected rays form an image ACB, where C is the position of the ray of the critical angle. The rays in to are reflected totally in the interface and the rays in B are partially reflected and partially refracted inside S. This way the optic image it is divided into illuminated area to and a dark area B. The position of the limit C among the areas to and B shows the value of the critical angle and therefore of the refractive index of the solution of the process. The refractive index is usually increased whilst increasing the concentration.

In the Figure 2 shows a summary of the total approximation of the RAWN each step can be divided into different actions and calculations, the first part of the algorithm has to do with the estimation of the activation weights

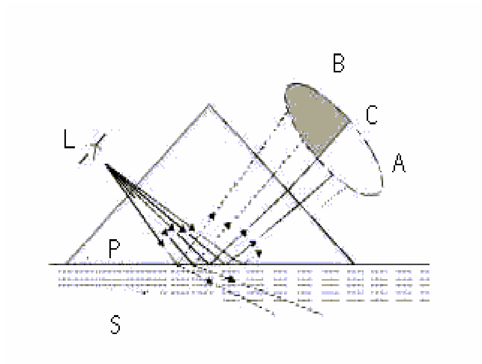

Fig. 2. Analyzer of the concentration of phenol

This is based on the construction of local linear models, but to construct these linear models, the dataset first needs to be partitioned into different subsets, which will be used for the estimation of a particular local linear model, to avoid saturation of the activation function, these subsets need to be scanned, this is the second step of the algorithm, the third step is with the parameters of these local linear models that must be calculated by linear quadratic techniques, the resulting parameters of the local linear models are used as the activation weights of the neural network, now that the weights have been calculated, the final step of the RAWN training process is the estimation of the output weights by standard linear quadratic techniques.

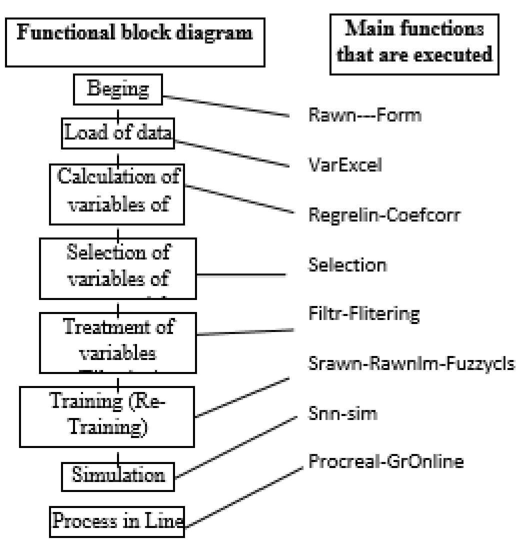

Fig. 3. Block Diagram and Main Functions of the Smart Sensor [10]

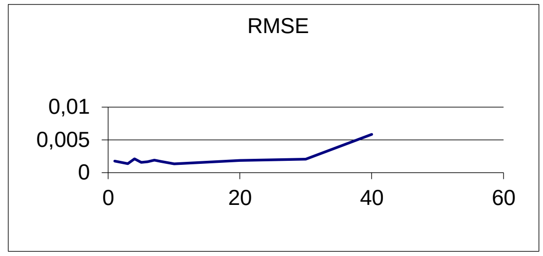

***Figure 3**. RMSE by Number of Neurons with Regression.*

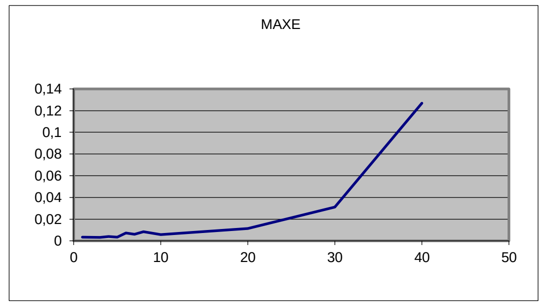

***Fig. 4**. MAXE by Number of Neurons with Regression.*

TABLE I

Results of the experiments with the model by correlation and dispersion experiment results for model [10]

# NEUR	RMSE	MAXE
3	0.0010291	0.0027133
5	**0.0011054**	**0.0024877**
10	0.003029	0.012585
12	0.00096497	0.012741
15	0.0036674	0.0073696
20	0.00072544	0.0071936

TABLE II

Resultados de los experimentos con el modelo por el experto

# N	RMSE	MAXE
5	0.0019238	0.003634
10	0.0017794	0.0037834
12	**0.0016122**	**0.0035634**
15	0.0021772	0.0071826
20	0.0035932	0.020569

TABLE III
Experiment results for models

MODELS	#N	RMSE	MAXE
CORRELATION-DISPERSION	5	0.0010612	0.0034794

For the RAWN Training Method. Which allows to obtain the parameters of the architecture neural network, the analysis of the behavior by complete training, with the optimal parameters found for the RAWN, to determine the appropriate network is considered the number of neurons in the hidden layer, samples required for the Training and the number of steps back, For each training the RMSE (Error RMS) complemented with the MAXE (Maximum Error: with the validation data to determine the experiments with the best performance corresponding to the optimal parameters.

The computational contribution was obtained in the reduction of the execution time necessary for the training that the algorithms require determination of the parameters of the neural network.

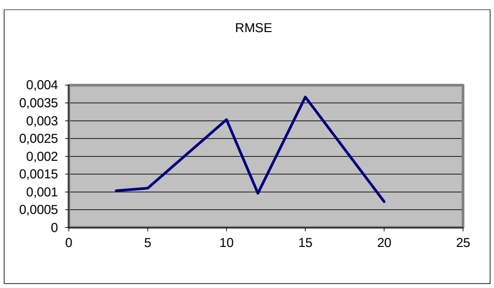

Fig. 5. *RMSE by Number of Correlated and Dispersing Neurons.*

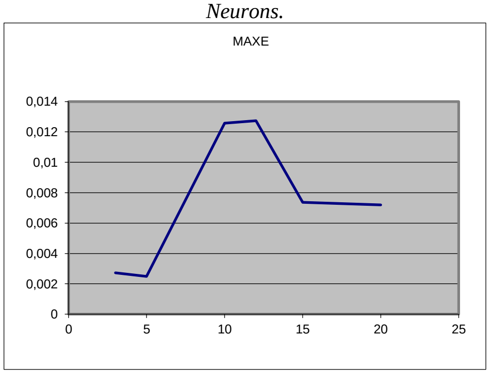

Fig. 6. *MAXE by Number of Correlated and Dispersing Neurons*

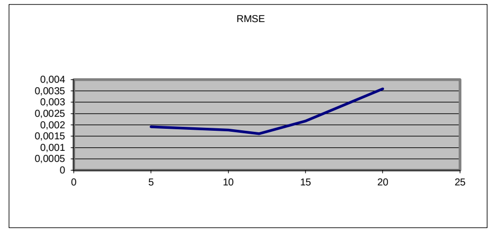

Fig. 7. *RMSE for Expert Model*

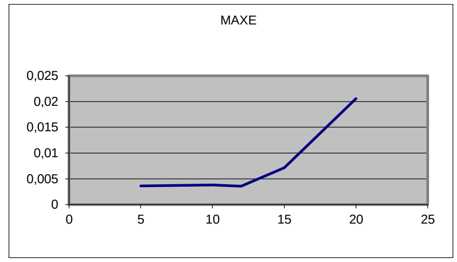

Fig. 8. *MAXE for Expert Model*

Proved of possible linear, sign treatment to filter noise eliminate false data, training-validation and tests for simulation off line and on-line with the real process. The measurement of the RMS error is used and the Maximum opposing Error, mainly in the validation phase to be used as the comparison parameter that allows for the evaluation of the acting of the obtained pattern.

TABLE VI
Input weights

W1	V6	V7	V10	V14	V15
N#1	-0	6	4	3	4
N#2	11	-6	-4	1	6
N#3	9	-7	6	-1	0
N#4	4	-6	1	3	5
N#5	9	-1	-2	2	-5
W1	V17	V18	V32	V44	V63
N#1	12	-10	342	63	-1071
N#2	-6	-14	-457	-58	312
N#3	-6	11	-65	12	1017
N#4	9	-8	-923	-126	117
N#5	6	-6	1036	-51	549

TABLE VII
Output weights

W2	0.033 0	-0.0532	0.028 4	0.0168	0.003 9

TABLE VIII
Results of the Regression Model Experiments

# NEUR	RMSE	MAXE
1	0.0017439	0.0033676
3	0.0013600	0.0031367
5	0.0015836	0.0035062
7	0.0019241	0.0061608
10	**0.0013473**	**0.0058143**
20	0.0018437	0.011341
30	0.0020754	0.031088
40	0.0058415	0.12686

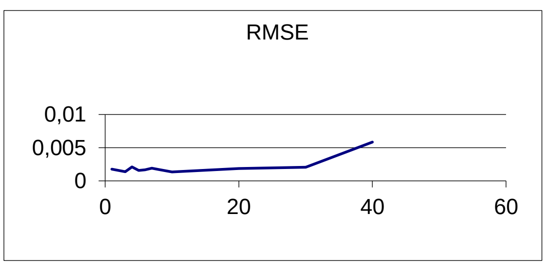

Fig. 9 *.RMSE for Número de Neuronas con Regresión.*

III METHODOLOGY BASED MOTHER CELLS

For the implementation of the methodology based on stem cell patterns (nanosensor-smart control-nanoactuator) a learning stage is required, with the GA procedure (in the search phase of the correct sequence), so it is implemented directly, replacing the "parent" device, which can be used as a reference element in a primary stage of implantation a summary of the operation of the cloned system, in this illustration it is seen, as the inputs are converted, thanks to "Fuzzy c -mean "in fuzzy clusters and these in turn are reflected in fuzzy sets.

Fig. 10. MAXE for # de Neuronas con Regresión.

TABLE IX

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The RAWN (neural network) [10]

# NEUR	RMSE	MAXE
3	0.0010291	0.0027133
5	0.0011054	0.0024877
10	0.003029	0.012585
12	0.00096497	0.012741
15	0.0036674	0.0073696
20	0.00072544	0.0071936

Fig. 11. RMSE by Number of Correlated and Dispersing Neurons

Fig. 12 MAXE by Number of Correlated and Dispersing Neurons

TABLE X

RMSE y MAXE For training in the area that covers the samples from 4000 to 5000

MODELS	#N	RMSE	MAXE
CORRELATION-DISPERSION	5	0.0010612	0.0034794

TABLE XI

Results Expert Model

# N	RMSE	MAXE
5	0.0019238	0.003634
10	0.0017794	0.0037834
12	0.0016122	0.0035634
15	0.0021772	0.0071826
20	0.0035932	0.020569

Fig. 13. RMSE for Expert Model

TABLE XII

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Comparison of Different Models

MODELS	#N	RMSE	MAXE
REGRESSION	10	0.0013473	0.0058143
CORRELATION-DISPERSION	5	0.0011054	0.0024877
EXPERT	12	0.0016122	0.0035634

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Fig. 14. MAXE for Experto Model.

Fig. 15. Behavior of the Cloned Sensor (Area of Training with 1000 samples and Validation of the remaining ones) [10]

After having this information in the form of a "chromosome", the sequence of genetic operators is applied, which converts the input information into "chromosomes" with the same data structure (antecedent and consequent).

The data set delivered by the cloning process is processed by the system, one of the important stages of this process is the defuzzification of a part of the "chromosome", so that it can have the value of the variable cloned in ranges of the universe of discourse and not in terms of belonging to fuzzy sets.

The modeling of nanotechnology systems equipped with nanosensors of phenol concentration, pressure and flow by top-down design methodology and the nanoinstrumentation parameters are presented in terms of membership of sets

IV. RESULTS AND DISCUSSIONS

The configuration of a polymer molecule is due to the nature of the tetrahedral carbon atoms which forms the basis of most polymeric structures. A system of these atoms is the amorphous state of a polymer, in contrast to the crystalline state that the molecules are most ordered. When interacting with a solvent, the various molecular polymer chains will be soaked in solvent. If there is little interaction of polymer it dissolves and is simply dispersed. If the interaction is strong, then the molecule bonds will easily disappear, since there will be a considerable number of solvent molecules surrounding the polymer chain. If the polymer / solvent interaction is equal to the intermolecular interaction then the resulting solution is known as an ideal solution. This polymer melt can also be viewed with an ideal solution since the solvent is simply a polymer of the same type as the solute for a polymer solution it is subjected

Electrospinning must have a sufficient degree of intermolecular interaction to cooperate with stress forces associated with the fiber deposition process.

The figure shows a schematic of the procedure for the synthesis of the solution that will be used for the respective tests

Fig. 16. Preparation process

The PVA used PVA-124, with a degree of polymerization of 2400 and a degree of hydrolysis of 98.41mol%, the solvent used was distilled water to be used. For preparation of the polymer Solutions of 6% 8% and 10% by weight of compound were made in a total of 90 grams taking into account the following amounts to be used:

TABLE XIII

Sampling References

6%	H_2O = 86.4 g
	PVA = 5.4 g
8%	H_2O= 82.8 g
	PVA = 7.2 g
10%	H_2O = 81 g
	PVA = 9 g

Using the analytical balance, the weights and measurements necessary to carry out the preparation process were determined, taking into account Table 1, where the sample values are shown in quantities used as a result of the experimental design for solutions of 6%, 8% and 10%

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VI. CONCLUSIONS

The use of the genetic mapping allows the design of quicker teams for the sequencing and with computer development the creation of the databases is possible to transmit, to store, to analyze and clone this information.

The artificial neural networks are able to manage complex and not linear problems, they can process information very quickly and they reduce the required computers effort in the development intensive computer of model, finding functional forms for empiric models as shown by that of our case with the cloned sensor.

One can obtain an excellent genetic mapping with neural networks in advance with only a layer of non-lineal neurons taking the activation random values, continued by a training of the values of having left by ordinary minimum square. Static and dynamic examples show the feasibility of this approach. As in any non-lineal identification, care should be taken to make sure that the excitement entrance used for identification, be in the same range of frequency and width like in the application. Later improvements they can be obtained for regularization of the values activation.

As a result, the software tool elaborated for such an end, can be used in the training of any system (entrance-exit) that seeks to be solved applying neural networks of this type. It has all the intermediate steps required as the attendance in the selection of variables for statistical methods that use the mathematical one required for the treatment of this class of stochastic processes

In the experimental validation, the electrical characteristics of the samples of the conducting polymer are considered in concentrations of 6%, 8% and 10% where it was established that as defined for the application in the manufacture of nanosensors by ISO standard TC 213 Which takes into account the geometric structure of the nanostructured nanomaterial and its main longitudinal dimension the spatial distribution of the obtained sample (lattice) determine its electrical conductivity in spite of its electrical anisotropy, the assembly on the surface of the nanowires is defined for conductivity at distances Greater than 200 nm being the nanoe structura obtained for the nanowires with 6% concentration of the polymer.

The modeling and simulation of the design of nanostructures surfaces with conductive polymer nanowires was done with software Molecular Workbench version where the runs of the quantum model were realized through the design based on response surfaces and the calculation of

Engineering in Nanotechnology of The quantum energy characteristics of the samples based on the equivalent circuit where Modeling the electrical behavior of conducting polymer nanostructures where a voltage is applied to the nanowires (source voltage) and to the surface (gate voltage) for the electrical characterization of polymeric fibers Obtained by electro-silting through the I / V curves obtained with computational nanotechnology for 1D in longitudinal conductivity

It is recommended to carry out the implementation of the nanosensors through development of functional replication based on stem cells and intelligent systems for manufacturing that allows replicas of imitation reproduced by generations of "chromosomes", representations of configurations of evolutionary algorithms, clustering in fuzzy sets And distributed control with deep neural networks of the initial population, information on performance functions of the equipment and / or installation, ordered according to a multiobjective function supported in the quantum model, with "genetic operators", tools that alter the composition Of the new chromosomes generated by the parents (initial population), during reproduction and includes: Mutation (generation of new information in a system), Crossing (information exchange between two systems), Investment (exchange information in the same system); In this way with the Model of evolutionary circuits can have the basic structures for the design of stem cells as a solution for the characterization of evolutionary circuits of micro- and nano-automats where mutation switching is substituted as a result of the change in the circuit of configurable logic blocks By mutable logic blocks.

Using the Bottom Up methodology for the implementation of adaptive nanosensor systems in fusion of sensor technologies and actuator functions in intelligent materials has resulted in a new technology: adaptronics or adaptive materials. The idea of this new technology is to use intelligent materials that act as sensors to detect, for example, changes in the environment such as pressure, temperature, humidity, and can respond to these changes in a controlled way by means of actuators i adaptronic, the sensor and the actuator are integrated in the same structure. The sensor detects changes in its environment, and sends this information to the control system, which produces a response signal and sends it back to the actuator. This device is, finally, in charge of performing the commissioned action.

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