OPTIMIZACIÓN DE RESISTENCIA A LA TENSIÓN EN PIEZAS DE POLIAMIDA-6 MOLDEADAS POR INYECCIÓN USANDO TÉCNICAS DE REDES NEURONALES Y PROGRAMACIÓN NO LINEAL

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ABSTRACT:
The main objective of this research is the optimization of tensile stress of injection molded parts of polyamide-6 to establish process conditions that maximize tensile strength of parts in a real industrial process. The methodology consisted in development of assays based on I-optimal experimental design to get a data base. Four parameters were considered as inputs: injection holding pressure, injection packing time, % wt virgin material and % wt recycled material.
Measurement of maximum tensile stress in parts was made according to ISO 527-1 standard.
Three models were developed by the techniques Response Surface Methodology, Back Propagation Neural Network and Generalized Regression Neural Network to predict parts maximum tensile stress.
Finally, the best model (with lowest forecasting error) was optimized by Trust Region Method Based on Interior Point Techniques for Nonlinear Programming to maximize tensile strength.
This proposed methodology is capable for modeling the process with low error and for stablish process conditions to obtain the maximum tensile stress on molded parts.
Keywords: Plastic Injection Molding; Tensile stress; Polyamid-6; Response Surface; Backpropagation Neural Network; Generalized Regression Neural Network; Nonlinear programming.

RESUMEN:
Esta investigación tiene por objeto optimizar la resistencia a la tensión en piezas de poliamida-6 moldeadas por inyección para establecer las condiciones que permitan maximizar el esfuerzo de tensión de piezas en un proceso industrial real. La metodología consistió en el desarrollo de ensayos basados en un diseño de experimentos tipo I-óptimo, para generar una base de datos. Se consideraron cuatro parámetros de entrada: presión de sostenimiento de inyección, tiempo de sostenimiento de inyección, % de material virgen y % de material reciclado. Las mediciones del esfuerzo máximo de tensión en las piezas se realizaron bajo la norma ISO 527-1.
Fueron desarrollados tres modelos con las técnicas Superficie de Respuesta, Red Neuronal Back Propagation y Red Neuronal de Regresión Generalizada para predecir el esfuerzo máximo de tensión. Finalmente se optimizó el modelo con el menor error mediante la técnica de región de confianza basado en técnicas de punto interior para programación no lineal, para maximizar la resistencia a la tensión.
Con esta propuesta metodológica es posible modelar el proceso con bajo error y establecer las condiciones que permiten alcanzar el máximo esfuerzo a la tensión de las piezas inyectadas.

Palabras clave: Moldeo por inyección de plásticos; Esfuerzo de tensión; Poliamida-6; Superficie de Respuesta; Red Neuronal de Retro-propagación; Red Neuronal de Regresión Generalizada; Programación no lineal.

1.- INTRODUCTION

The maximum tensile stress of injection molded parts is an important quality characteristic for the automotive industry, for example, in polyamide-6 (PA6) gears (components of automotive starting engines), due to the stresses they endure during their use. The Mexican company Troquelados Rex, S.A. de C.V. manufactures these gears and seeks to identify the effect of mixing recycled and virgin materials in the product's final tensile stress, and to know if this property is affected by the

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process variables Holding Pressure and Packing Time. This question motivated the present study, for application in a real world industrial process. This research compares the performance of three techniques to model and predict the effect of the process and material mix variables on the maximum tensile stress; the model with the best performance was optimized applying the Trust Region Method Based on Interior Point Techniques for Nonlinear Programming, seeking a process that engineers of the company can best use.

Injection molding is the most important industrial process in the manufacture of plastic products [1]. The mechanical properties of an injected part can be influenced both by the materials and by the process conditions. It is important for the industry to correctly establish these variables to get products with better quality, however the trial and error method is generally used to define their conditions. This method requires a large number of tests and a long expenditure of time; in addition, it does not guarantee to find the optimal conditions desired. There is a need to have reliable tools to model and evaluate by simulation the different scenarios in the process, in addition to optimizing the conditions of processing and mixing of materials to improve the quality of the parts. A reliable method to determine these conditions becomes key to improving quality.

Several techniques have been published to model and optimize the plastic injection molding (PIM) process. Some take advantage of the great capacity of current computers, such as those based on artificial neural networks, with good performance in complex, non-linear systems and with some level of imprecision [2], like most industrial processes. Several studies propose methods to simulate and optimize the effects of PIM parameters.

An investigation [3] applied Radial Basis Neural Networks (RBFNN) to analyze distortions in molded parts of polypropylene and proposes a modeling and optimization method combining RBFNN with quadratic sequential programming (SQP); data were obtained from a Taguchi Design of Experiments (DOE) considering process factors to minimize distortions. The performance of the proposed method was compared against the DOE Taguchi using the mean square error (MSE) criterion; the RBFNN showed a better performance.

Several studies apply Back Propagation Neural Networks (BPNN) to model the PIM; [2] combined this method with an Adaptive Neuro-Fuzzy Inference System (ANFIS) to predict mechanical properties of polyamide-6 composites by mixing EPR-g-MA elastomer and glass fiber, considering process parameters and concentration of components in the mixture. Their predictions adapted well to experimental data with low root mean square error (RMSE). Another study, [4], proposes a combination of BPNN with Genetic Algorithms (GA) minimizing shrinkage considering 5 process parameters. The authors generated a database for training. The model showed good predictions. Similarly [5], [6] and [7] applied BPNN considering process parameters and optimizing the quality of molded parts; [5] optimized the weight of parts, [6] minimized warping, while [7] optimized weight and length, calculated the prediction error and found good performance of the BPNN to model and predict the PIM. In a separate study, [8] combined BPNN with Self-Organizing Maps (SOM) as a dynamic system for predicting warpage in the PIM by comparing its performance (by RMSE measurement) against a simple BPNN; his proposal showed better performance.

Several researchers have studied PIM applying DOE, such as [9] that compared the prediction of a response surface model (RSM) against a BPNN by the MSE, evaluating surface roughness in an injection mold. They considered three machining variables; the BPNN presented better prediction than the RSM. On the other hand, [10] proposes an adaptive optimization method based on BPNN with expectation improvement function for PC/ABS parts, using a Latin Hypercube DOE to integrate a training database. They defined conditions to minimize warping.

Mechanical properties of parts injected with PA6 (Nylon) have been studied; [11] analyzed tribology properties in pieces of pure and fiber-reinforced PA6, optimized some parameters of the tribology assay by hybridization of Taguchi method, Gray Relational Analysis and Cukoo search algorithm, identifying statistical significance of the factors and minimizing friction coefficient and wear rate. On the other hand, [12] applied BPNN to predict mechanical and friction wear properties in fiber reinforced polyamide composites, optimizing performance of various network configurations and fiber concentration

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through measurement of error and computation time; they found that prediction can be improved if the training database is enlarged or if the network configuration is optimized.

2.- MATERIALS AND METODS

This research proposes a methodology with four stages: 1, mixtures with different concentrations of material were prepared and specimens were injected varying the PIM operation parameters, determining tensile stress and recording the information; 2, using experimental data, three mathematical models were generated: generalized regression neural network (GRNN), BPNN and RSM to relate the inputs with the response; 3, the model that predicts better was selected; 4, such model was combined with an optimization algorithm to get the levels of mixture and process parameters to maximize tensile stress.

Injection of specimens.

Polyamide-6 specimens were manufactured in a Demag-Ergotech 50-270 molding machine. The experimental runs were based on a DOE type I-optimal combined (including mixing and process factors) and randomized with three replications, using DesignExpert software. I-optimal designs minimized the average prediction variance; these designs type are considered appropriate for mixing experiments. This computer-generated design was used because it reduces the number of experimental runs by the optimal localization of experimental points.

The experimentation was performed at Troquelados Rex industrial plant: this ensured that information came from a practical industrial application environment. To prepare material, batches were weighed and mixed until they were completely homogenized; specimens were injected purging the equipment with each change of material. The first 10 pieces of each run were discarded to allow the process to reach a stable state. All specimens were kept at 22 degrees Celsius for 48 hours before measuring their tensile strength.

Table 1 presents the experimental plan with the factors and levels considered; it was expanded with 3 repetitions to add more runs and get more detailed information on the process behavior. That totals 75 tests for training the models. The level 1.5 s of the packing time (run 21), apparently anomalous, was automatically defined by the I-optimal method software through additional points (which can be central, axial, or average) to obtain the maximum information. For greater statistical certainty, 17 additional corroboration tests were performed (with material mix concentrations different from those used in the training runs), defined under an empirical criterion, seeking to be different from those of training to corroborate the predictions of the models, totaling 92 experimental test specimens. All other factors involved in the PIM remained fixed during the experiments. The specimens were tensile tested in a Zwick / Roell-Z050 universal machine, with a 5 kN load cell, using mechanical closing jaws at constant speed of 50 mm / min. A long-travel extensometer with initial length 50 mm was used. The measurements were made under the ISO527-1 standard, obtaining the maximum tensile stress from the stress-strain curve data. All measurements were developed under the same conditions.

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Table 1. Input parameters and their levels. Gray highlight text shows the corroboration runs.

Experiment	% wt Virgin polyamide-6	% wt Recycled polyamide-6	Holding pressure (MPa)	Packing time (s)
1	100	0	90	1
2	25	75	110	2
3	50	50	110	1
4	100	0	90	3
5	0	100	110	1
6	25	75	90	2
7	50	50	90	3
8	50	50	110	1
9	50	50	90	1
10	0	100	110	3
11	100	0	110	1
12	50	50	110	3
13	50	50	110	3
14	0	100	90	3
15	75	25	100	2
16	0	100	90	1
17	50	50	110	1
18	25	75	100	3
19	100	0	110	3
20	50	50	90	3
21	0	100	100	1.5
22	50	50	90	1
23	75	25	110	2
24	75	25	90	2
25	75	25	100	3
26	66	33	100	3
27	66	33	100	1
28	66	33	90	1
29	66	33	90	3
30	66	33	110	1
31	66	33	110	3

Percentage weight concentrations of virgin and recycled PA6 were considered to know if mixture factors affect tensile strength: due to degradation of recycled material, it would be expected that the greater concentration of recycled material decreases the tensile strength. The injection parameters Holding Pressure and Packing Time can influence the compaction of polymer chains and crystallization while the temperature of the polymer decreases; by increasing these factors it would be expected to achieve better mechanical tensile properties, however, when combining factors of material and process, an optimum point of maximum resistance can be achieved. This is phenomenologically complex to determine by trial and error, so a methodology is proposed that uses empirical models for the simulation of relationships between the input factors and the response of interest, which was subsequently optimized for maximization. With this methodology it is possible to obtain knowledge of the behavior of the process and determine the levels of the factors that produce the best quality in the parts. **Figure 1** shows the proposed methodology.

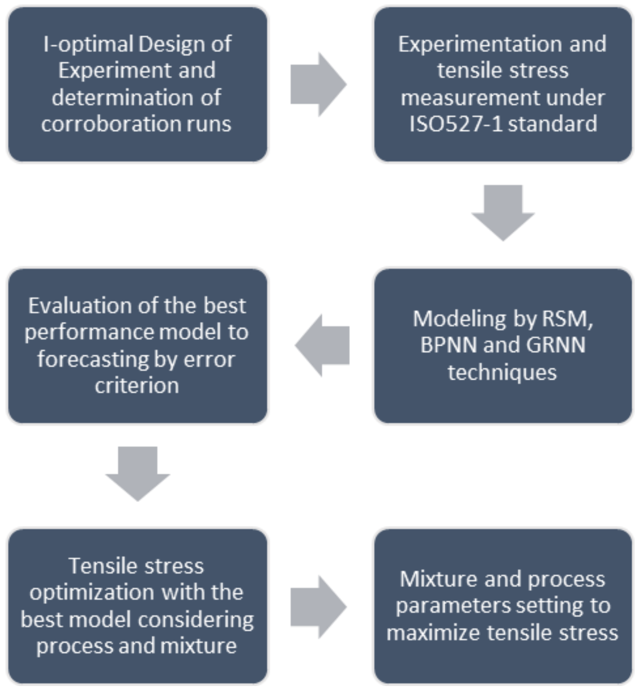

Figure 1. Steps followed in study methodology

Modeling.

Three modeling techniques were compared: BPNN, GRNN and RSM using software for their generation, training, and validation. The levels considered for the training were: five levels of weight concentration of PA6-virgin (range 0-100%); five levels of complementary concentration in weight of PA6-recycled (range 0-100%); three levels of holding pressure (range 90-110 MPa) and three levels of packing time (range 1-3 s); these ranges were determined through a pre-experimentation that allowed to achieve parts within specification.

BPNN.

Neural networks are mathematical structures to process information through several interconnected neurons that respond to an input value with variable weights, boundaries and transfer functions. The BPNN has good capacity for nonlinear interpolation obtaining detailed mappings of the experimental internal behaviors. This type of network has been used extensively in engineering, prediction and optimization applications. The network used has four inputs, an internal layer with 10 neurons, and the output layer (**Figure 2**).

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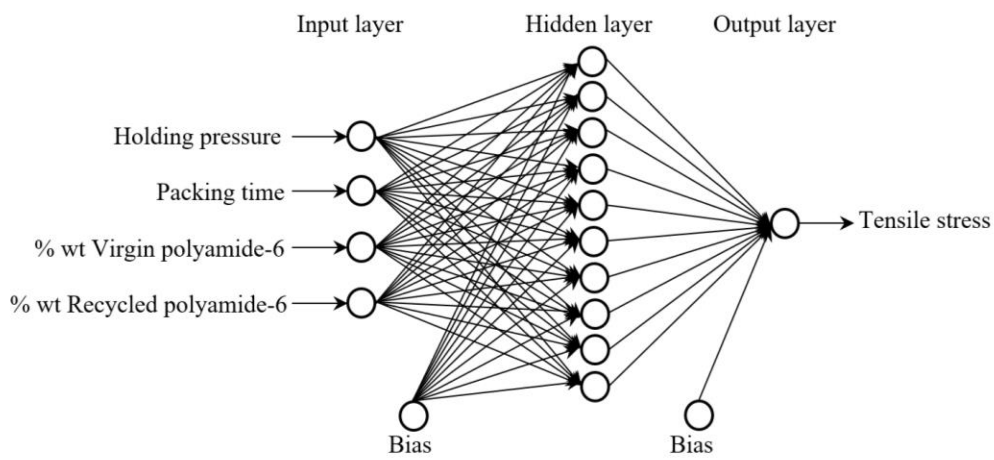

Figure 2. Architecture of the BPNN applied in this study.

In this network, each neuron receives the total of entries from all the preceding neurons, using the following mathematical expression

$$\mathbf{Net}_j = \sum_{j=0}^{N} \omega_{ij} x_i \qquad (1)$$

Where Net $_j$ is the total of inputs, N the number of neurons in the hidden layer, and ω_{ij} the weight factor of the connection generated in the network structure; each neuron generates an output that is processed through a transfer function; for this study, the following hyperbolic sigmoidal tangent function (Tansig) was used:

$$\mathbf{Response}_j = \boldsymbol{f}(\mathbf{Net}_j) = \frac{1-e^{-Red_j}}{1+e^{-Red_j}} \qquad (2)$$

This network is the most common of those reported in the literature, it is widely validated, so it was considered as the first option to be implemented for problems of this nature.

GRNN.

The GRNN is a special type of network that has a defined architecture and is frequently applied for approximation of complex nonlinear functions; it has three layers: one input, one hidden with radial basis function (RBF) and a special linear output. The hidden layer has a quadratic exponential transfer function, and the output layer has a linear function (**Figure 3**). This network is used to create a generalized regression in y; its dispersion-σ parameter (SPREAD) is usually assigned a value slightly less than 1 to obtain a function that can be adjusted to the individual data in an accurate way, obtaining characteristics such as good adjustment and higher training speed. A smaller spread fits the data better, but the model is less smoothed, so the methods with RBF can achieve exact interpolation, that is, the regression surface can pass through each of the sampling values. This allows good interpolations when the inputs, instead of generating precise outputs, are noisy. [13] showed that networks with RBF have the best approximation properties, which does not happen with other types of networks, such as the Multilayer Perceptron.

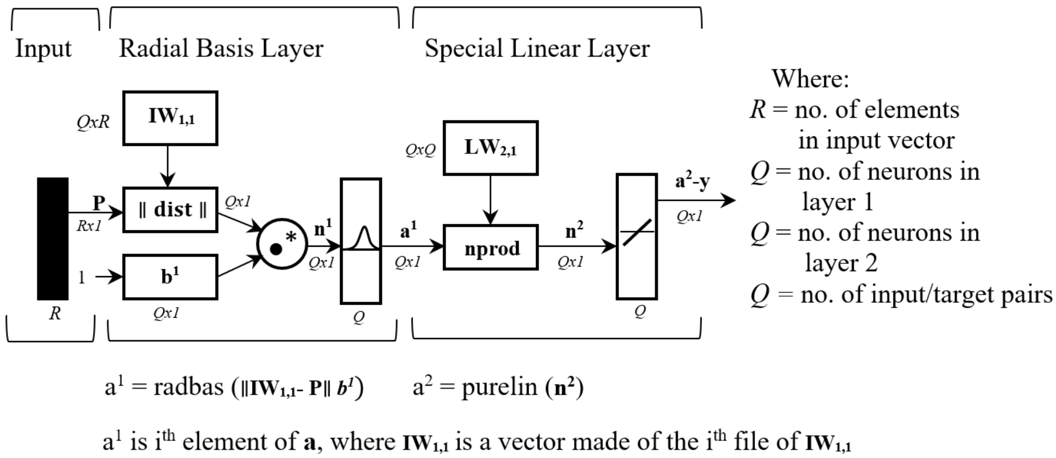

Figure 3. Network architecture, GRNN

The transfer function of the inner layer in neural networks with RBF is:

$$f\,(\mathrm{Net}_{\,j}) = e^{-n^2} \qquad \phi\,(x) = \exp\left(-\frac{x^2}{2\sigma^2}\right), \tag{3}$$

Generalized Regression Networks are mainly applied to adjust functions; however, they could generate a function with little smoothing in problems of high non-linearity; nevertheless, it is possible to adjust the smoothing of the function by means of its dispersion parameter (spread-σ), which represents the radial distance of a vector from the experimental point to the predicted. It is imperative to note that, a low dispersion generates a slightly smoothed function, but higher precision on the model with respect to the training data, while a high σ value generates a smoother function, but with the disadvantage that the accuracy of the model is lost with respect to the training data. Recalled that, generally a value slightly less than 1 is used; this study used a spread of 0.7199, since it fits better with the data used.

The GRNN was implemented as a model for prediction, given its characteristics, and considering that by varying the spread, the network can achieve good predictions and is very fast training; It is considered the most efficient network in the computation process, because it requires less training time. The GRNN algorithm was programmed in Matlab-2017a with an Intel-i7 processor.

RSM.

The RSM is an advanced DOE technique used to determine optimal values when modeling processes that allow an empirical description of behaviors; RSM is commonly used to map interrelations between parameters and responses with quadratic interactions. This model has the advantage that the interaction factors have a direct value in the model, which directly indicates its effect on the mathematical model, which is a multiple linear system that interrelates all the factors and draws its quadratics with their respective relationships. The general equation that represents a quadratic double interaction function with two factors is:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_{12} x_1 x_2 + \beta_{11} x_2 x_1^2 + \beta_{22} x_1 x_2^2 + \beta_{11} x_1^2 + \beta_{22} x_2^2 \tag{4}$$

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This equation is only illustrative of the RSM model structure. It was not used, since it only considers 2 parameters, while the study problem includes 4. Design-Expert software was used to obtain the RSM model; a quadratic model was applied to the mixture, and an interaction of two factors (2FI) for the process variables.

These three models, BPNN, GRNN and RSM, were chosen because of their individual advantages, depending on the type of problem analyzed. From the spectrum of methods for modeling problems, with this three models it is possible to cover a wide range of situations to model manufacturing processes; summarizing each models´ main advantages: the RSM allows the observation of interaction effects of independent parameters in the response and generates a model equation that helps to clarify the information of the process; RSM is an efficient model, with good prediction properties, although its predictions can become affected sometimes when the adjusted response becomes negative. The BPNN has good performance for modeling and prediction in linear and nonlinear problems; also minimizes the error with each backward propagation cycle in which the weights are adjusted, however it requires a high training time. The GRNN is a probabilistic network that provides estimates of continuous variables and converges to the underlying regression surface (linear or non-linear). Even with scattered data in a multidimensional measurement space, the algorithm can provide discretized (smoothed) transitions between one observed value and another, or achieve exact interpolation, which passes through each of the training points. This latter advantage seen in GRNN gives it flexibility to adapt to the problem by varying its dispersion parameter. The GRNN can solve any problem of approximation of functions, it is a universal approximator for discrete functions, allowing to estimate any problem of continuous variable when there is enough data.

In contrast, the study [14] applied five methods to model a process and evaluate its prediction capabilities based on the error: Single hidden layer feedforward neural network (SHLFFNN), is the simplest neural network and can operate as linear or logistic regression, so it is not frequently used instead of these two regression techniques; Gradient Descent Back propagation neural network (GDBPNN) uses gradient descent algorithm to modify weights; Gradient Descent Back propagation with momentum neural network (GDBPMNN) can overcome problems with local minimums; Back propagation with Weight decay neural network (BPWDNN) can reduce the long training times of the BPNN, also prevents over-training; the last of the five methods, Quantile regression neural network (QRNN) combines regression of quantiles with neural networks through regularization parameters that penalize the complexity of the network to prevent over-training; However, these five techniques do not have the advantages of flexibility, rapidity, universal approximation capability, nor show interaction effects, characteristics that do present the three techniques used in this investigation.

Models comparison.

After obtaining the models, the same conditions of the confirmation runs were simulated applying the three modeling techniques. 3D surface and contour graphs for each model were generated. With the predictions obtained, the prediction error was calculated to identify which model predicts the response better. Proceeding the identification of our best response model, the optimal operating parameters were later determined using such model.

Optimization

The Trust Region Method Based on Inner Point Techniques for Nonlinear Programming (TRIPTNLP), is a mathematical programming optimization technique to find the minimum of a non-linear multivariable function with restrictions. This technique is based on finding a feasible starting point within a solution region, defining a direction of movement preserving the feasibility up to a point of reduction of the objective function and finding the optimal point to stop the algorithm. This methodology is based on a system of restrictions that allows optimization in a specific region and uses a non-linear strategy, guaranteeing that regardless of the function topology, the respective minimum will be reached. This hybrid algorithm consists of the linear search calculation coupled to a search that uses a conjugate gradient calculating direct factorization, guaranteeing that the search advances to a stationary point [15]. Next, the solver for non-linear programming is presented: Find the minimum of a problem specified by:

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$$\min_x \; f(x) \text{ such that, } \begin{cases} c(x) \leq 0 \\ ceq(x) = 0 \\ A \cdot x \leq b \\ Aeq \cdot x = beq \\ lb \leq x \leq ub, \end{cases} \quad \text{where,}$$

b and *beq* are vectors, *A* and *Aeq* are matrices, *c(x)* and *ceq(x)* are functions that generate vectors, and *f (x)* is a function that generates a scalar. *f (x)*, *c(x)*, and *ceq(x)* can be nonlinear functions. *x*, *lb*, and *ub* can be considered as vectors or matrices. The TRIPTNLP method was applied in combination with the modeling method that presented the lowest error, to identify the optimal point that allows to maximize tensile stress and to define the conditions of the input factors that allow it to be achieved.

3.- RESULTS AND DISCUSSION

Figure 4 shows tensile measurements results of the 92 experiments performed, corresponding to 75 training and 17 validation runs. With this result, the three models corresponding to the BPNN, GRNN and RSM techniques were generated.

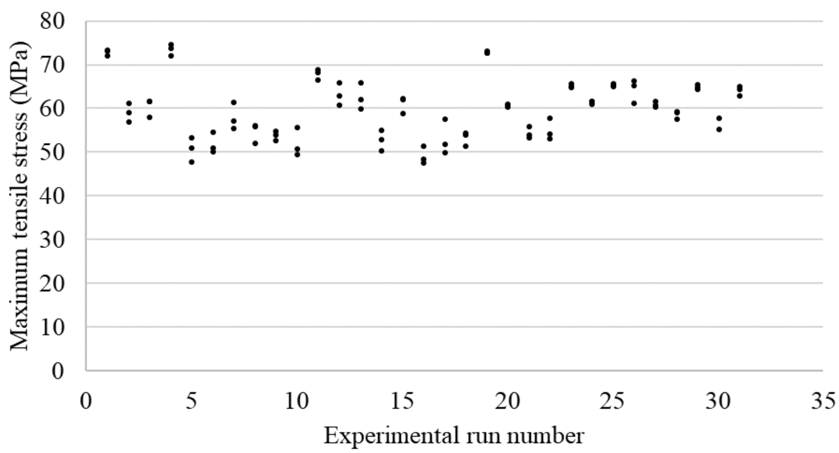
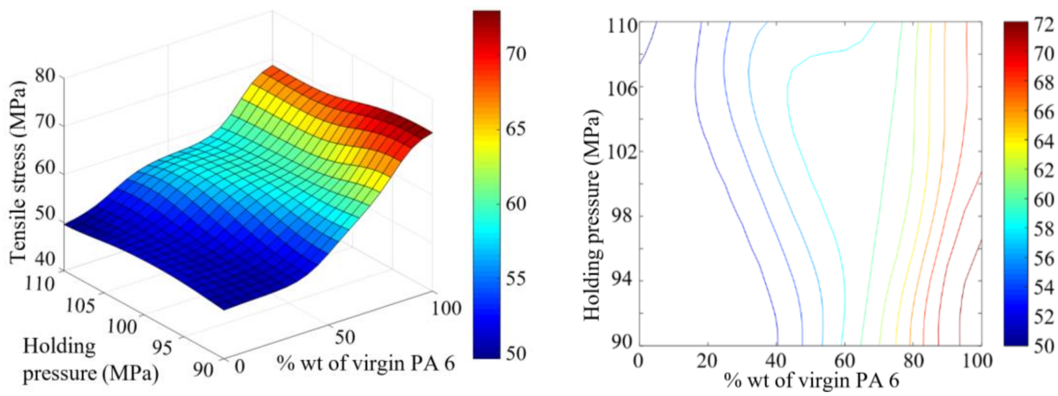
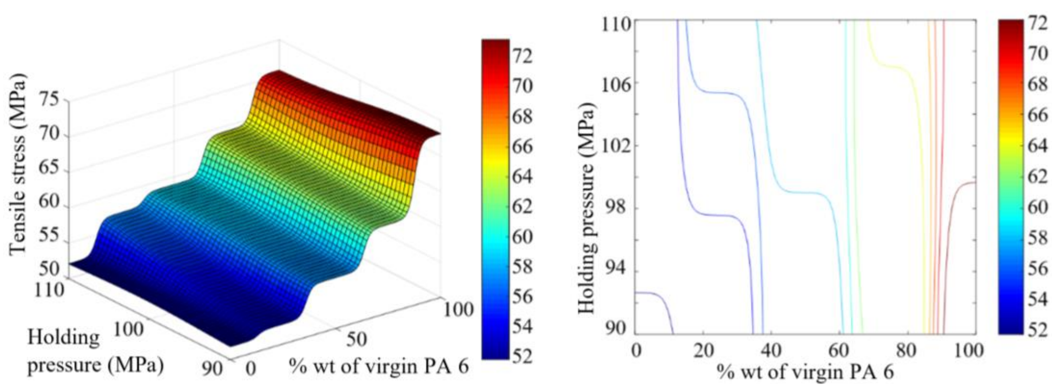


Figure 4. Results of tensile tests corresponding to Table 1.

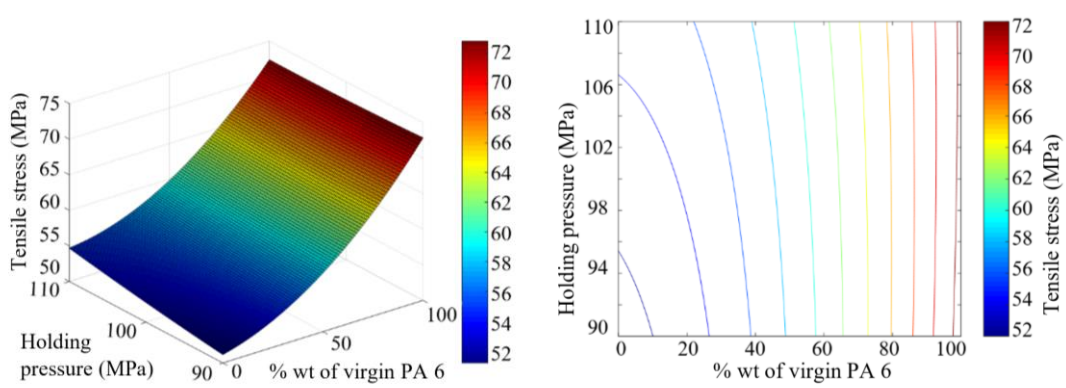
Simulation results are shown at **Figure 5**, the 3D surfaces and contour graphs for each model are presented. Section (a) shows the surface response of the model BPNN, represents on the vertical axis the maximum tensile stress and on the horizontal axes, holding pressure and mixture concentration. It is possible to observe a slightly smoothed surface with an evident increase in tensile strength when increasing the percentage of virgin material. Each graph in **Figure 5** shows a constant packing time of 2 s.



a) 3D model of the BPNN method with 2 s packing time



b) 3D model of the GRNN method with 2 s packing time and spread 0.7199



c) 3D model of the RSM method with 2 s packing time

Figure 5. 3D models and contour graphics, obtained with the methods (a) BPNN, (b) GRNN and (c) RSM

Section (b) shows the 3D surface of GRNN model. Analogous to the previous case, the horizontal axes represent holding pressure and concentration of virgin material, and the vertical axis represents the maximum tensile stress. The surface of the GRNN method shows a stepped surface with slight smoothing, which could generate, in theory, a good adjustment of the model in relation to the experimental measurements, since the regression is well adjusted with respect to the training points. We can see an increase in tensile strength when increasing the concentration of virgin material. Section (c) shows the 3D surface for the RSM. The axes of the graphs follow the same logic of the previous cases; a very smoothed curve is observed, and the increase in tensile strength is evident when using a higher percentage of virgin polyamide-6.

Validation tests.

Confirmatory experimental runs were performed with different material mix percentages from those used in the training assays; each confirmation run was measured under the same conditions as the training run, obtaining a new set of measurements to evaluate by comparison against the prediction performance of each modeling technique. The performance was evaluated using five different error criteria. **Table 2** presents the results comparing experimental measurements against predictions. The best prediction performance was obtained by the GRNN method with absolute mean error (MAE) of 1.81, average error percentage (MPE) of 3.03, RMSE of 2.40, relative square error (RSE) of 0.56, and coefficient of determination (R2) of 0.50, followed by the RSM and BPNN models. These results agree with that reported by [16], which found better prediction ability of the GRNN compared to the BPNN.

Table 1. Prediction error for confirmation runs.

% virgin PA6	% recycled PA6	Holding pressure (MPa)	Packing time (s)	Measured tensile stress (MPa)	Predicted tensile stress (MPa)		
					RSM	RBFN	BPN
66	33	100	3	65.53	64.13	64.08	63.32
66	33	100	3	66.40	64.13	64.08	63.32
66	33	100	3	61.36	64.13	64.08	63.32
66	33	100	1	61.75	59.14	61.71	59.49
66	33	100	1	61.04	59.14	61.71	59.49
66	33	100	1	60.58	59.14	61.71	59.49
66	33	90	1	59.23	58.64	61.54	60.73
66	33	90	1	57.83	58.64	61.54	60.73
66	33	90	1	59.36	58.64	61.54	60.73
66	33	90	3	55.33	62.44	61.54	63.36
66	33	90	3	57.89	62.44	61.54	63.36
66	33	110	1	65.66	59.64	65.31	57.69
66	33	110	1	64.63	59.64	65.31	57.69
66	33	110	1	64.99	59.64	65.31	57.69
66	33	110	3	65.20	65.83	65.31	65.15
66	33	110	3	63.07	65.83	65.31	65.15
66	33	110	3	64.61	65.83	65.31	65.15
				MAE	2.77	1.81	3.31
				MPE	4.49	3.03	5.37
				RMSE	3.42	2.40	4.22
				RSE	1.13	0.56	1.72
				R^2	0.0176	0.50	8.18E-07

The applied performance criteria facilitate the comparison of predictions respect to experimental values obtained with confirmation tests, evaluating the models' goodness of fit, for that reason the RSM and BPNN models presented a greater error, because they were not able to predict some experimental values of tensile stress with sufficient precision in comparison with GRNN model. **Figure 6** shows a forecasting comparison respect to the 17 confirmation runs; the GRNN model predicts the response with less error, showing better ability to model different training conditions compared to the other two methods; such model presents an acceptable level of error, which could be considered useful for the prediction of tensile resistance in the PIM. The causes that produce prediction errors are possibly the result of variables not considered during modeling.

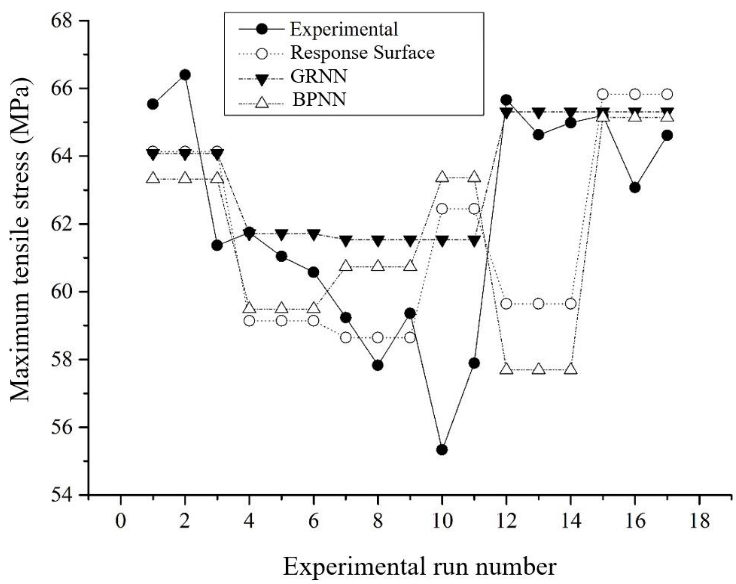


Figure 6. Forecasting comparison.

The GRNN model was used in combination with the optimization algorithm TRIPTNLP to identify the optimum point that maximizes tensile stress of the molded parts. The result of this hybridization of techniques is shown in **Figure 7**, which shows the optimal point. The result of the combined algorithm defines the settings of parameters (conditions) that allow reaching such optimal point, resulting in values of 99.99% of virgin material in the mixture, 90 MPa of holding pressure and a packing time of 3 s, which allows reaching a maximum tensile stress of 73.17 MPa.

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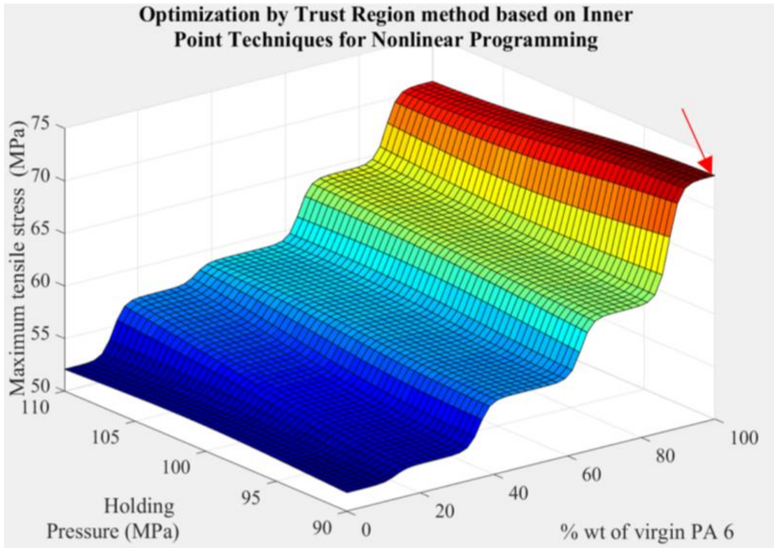

Figure 7. PIM process optimization. Red arrow shows optimal point.

This result is consistent with the intuitive logic of the phenomena that occur in the injection molding process, since the increase in holding pressure and packing time generate more crystallization and compaction of polymer chains as the part cools and solidifies; in addition, a higher percentage of virgin material implies less material with degradation, promoting better mechanical properties.

4.- CONCLUSIONS

PIM process, like some manufacturing processes, implies multiple variables that can affect the quality of the product. It is complex and stochastic in nature; its modeling and the optimization of its parameters are important challenges. An effective way to solve this problem is to identify the relationships between the performance of the process and its controllable input parameters by modeling the process through mathematical techniques and their optimization using algorithms [17].

The proposed methodology combines the individual advantages of three modeling techniques: BPNN, GRNN and RSM; its application and the selection of the best one, could solve some disadvantages that they present separately. When selecting the best model, the techniques that do not have a good fit for the type of problem studied are discarded. This advantage gives the proposed methodology a more general character for its applicability, in comparison with other individual methods reported in the literature with good performance in specific applications, but not in others: as the statistical regression that could not accurately describe the complex relationships non-linear of some problems, or fuzzy set theory, which is preferable to apply only when expert knowledge supports to define objective functions and rules, or the Taguchi method, which could have problems in representing important effects of interaction between variables in the domain of the proposed design [17].

The proposed methodology allows to study problems with combined factors of mixture and process; its optimization technique has the advantage of guaranteeing the location of the global optimum, in comparison with other techniques that may have problems with local minimums or give sub-optimal solutions, such as GA or Particle-Swarm Optimization (PSO) [17]. The main disadvantage of the proposed methodology is that it is laborious because it involves determining factors,

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designing and executing experimentation, generating and analyzing three models to choose the best one, in addition to the optimization process. The need to evaluate its performance with other types of problems is visualized.

The optimal conditions were defined to achieve the greatest tensile stress possible for the case study presented; it would seem obvious to an expert in plastics injection that a higher concentration of virgin material would produce more resistant parts, but this methodology could be applied in different cases where the optimal conditions are not evident at first sight. This study allows the company to propose different scenarios through simulation, with which it could meet the customer's quality requirements with acceptable precision and balance the percentages of virgin and recycled materials according to their costs.

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