Optimization of injection molding process parameters by a hybrid of artificial neural network and artificial bee colony algorithm

Optimización de los parámetros del proceso de inyección de plásticos a través de un híbrido de redes neuronales artificiales y el algoritmo de la colonia artificial de abejas

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Abstract

This paper presents a hybrid of artificial neural networks and artificial bee colony algorithm to optimize the process parameters in injection molding with the aim of minimize warpage of plastic products. A feedforward neural network is employed to obtain a mathematical relationship between the process parameters and the optimization goal. Artificial bee colony algorithm is used to find the optimal set of process parameters values that would result in the optimal solution. An experimental case is presented by coupling Moldflow simulations along with the intelligent schemes in order to validate the proposed approach. Melt temperature, mold temperature, packing pressure, packing time, and cooling time are considered as the design variables. Results revealed the proposed approach can efficiently support engineers to determine the optimal process parameters and achieve competitive advantages in terms of quality and costs.

---------- *Keywords:* Artificial bee colony algorithm, artificial neural networks, injection molding, optimization of process parameters, finite element simulation

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Resumen

Este estudio presenta un híbrido de redes neuronales artificiales con el algoritmo de la colonia artificial de abejas para optimizar los parámetros del proceso de inyección de plásticos con el objetivo de minimizar la deformación en productos plásticos. Una red neuronal de propagación hacia adelante es empleada para obtener una relación matemática entre los parámetros del proceso y el objetivo a optimizar. El algoritmo de la colonia artificial de abejas es usado para encontrar el conjunto óptimo de valores de los parámetros que resultarían en la solución óptima. Un caso experimental es presentado acoplando simulaciones de Moldflow junto con los esquemas mencionados con el fin de validar el enfoque propuesto. La temperatura del plástico, temperatura del molde, presión de empaque, tiempo de empaque, y tiempo de enfriamiento son consideradas como las variables de diseño. Los resultados revelan que el enfoque propuesto puede eficientemente apoyar a ingenieros a determinar los parámetros óptimos y alcanzar ventajas competitivas en términos de calidad y costos.

---------- *Palabras clave:* Algoritmo de la Colonia Artificial de Abejas, Redes neuronales artificiales, Inyección de plásticos, optimización de los parámetros del proceso, simulación de elemento finito

Introduction

Injection molding is a challenging process for manufacturers and researchers to produce plastic products at the lowest possible cost. Serious quality problems and high manufacturing costs are generally caused by parameter manipulation. Previously, determination of the process parameters in injection molding depended on the abilities of operators; that is, trial-and-error processes which relied greatly on the skills and experience of the technical personal. However, trial-and-error is costly and time consuming, and it cannot be tolerated in the face of global competition where it is necessary to produce faster and cheaper with high quality standards. Process parameters optimization is regularly carried out in the manufacturing field nowadays, specifically setting the optimal initial process parameters.

In the last years, several researchers have been attracted in optimizing the process parameters in injection molding. For instance, Mok et al. [1] developed a system for the determination of initial process parameters based on a hybrid neural network-genetic algorithm approach. Kurtaran et al. [2] presented a study to minimize the warpage for a bus ceiling lamp base by exploiting the advantages of finite element analysis, neural networks, and genetic algorithm to find the optimum process parameter values. Spina [3] presented a work that minimizes the product warpage by integrating artificial neural networks and Particle Swarm Optimization (PSO) algorithm to optimize the process parameters automatically. Kurtaran and Erzurumlu [4] introduced an optimization method by integrating finite element analysis, response surface methodology, and genetic algorithm to minimize warpage of thin shell plastic parts. Ozcelik and Erzurumlu [5] presented a study that combines ANOVA with artificial neural networks and genetic algorithm to find the optimum process parameter that minimizes warpage of thin shell plastic parts. Shen et al. [6] proposed a method to improve the quality index of the volumetric shrinkage by combining artificial neural network and genetic algorithm. Deng et al. [7] proposed an approach to determine the optimal process parameter setting by applying Taguchi's parameter design method, regression analyses, and the Davidon-Fletcher-Powell method. Gao and Wang [8] proposed an optimization method using the Kriging model to minimize warpage. Chen et al. [9] presented an approach that integrates Taguchi's parameter design, neural networks, and genetic algorithms for determining the optimal process parameter settings to reduce variations in the product length and weight. Gao and Wang [10] proposed an adaptive optimization method based on Kriging surrogate model to minimize warpage on molded parts. Altan [11] (2010) presented a work for minimizing shrinkage by finding the optimal injection molding conditions by Taguchi's design of experiments and neural networks. Deng et al. [12] presented a hybrid of mode-pursuing sampling method and genetic algorithm to minimize warpage. Farshi et al. [13] presented a study to find the optimum process parameters by using sequential simplex algorithm and finite element analysis to minimize warpage and volumetric shrinkage of a thin shell part. Huang [14] presented an optimization method by using ant colony algorithm for exploring optimal parameters in order to minimize warpage of plastic parts. Yin et al. [15] proposed a method that combines a back propagation neural network and genetic algorithm to optimize the process parameters in order to optimize warpage and energy consumption in injection molding.

This study presents a hybrid of artificial neural network and artificial bee colony algorithm as an alternative approach to find the optimal initial process parameters in injection molding with the aim of minimizing warpage of molded products. Artificial Bee Colony (ABC) algorithm is an optimization algorithm based on the intelligent behavior of honey bee swarm that can be used for multivariable and multimodal function optimization [16]. Artificial neural networks are employed to establish a mathematical approximation between the process parameters and optimization goal in order to replace the expensive and time consuming simulation analysis [10]. Thus, a predictive model for warpage is constructed based on artificial neural networks and finite element analysis software Moldflow. Five process parameters are considered in this study for being studied for many researchers and for being considered significant in the warpage of molded products; therefore, melt temperature, mold temperature, packing pressure, packing time, and cooling time are considered to be the design variables [2-5,9,10,12,13,15]. Likewise, warpage optimization is considered for being one of the most typical and noticeable defects, which impacts appearance and product usage [2,4,5,10,12-15,17]. The following section gives a brief overview of the ABC algorithm; then, the proposed approach is described in section 3. Next, an experimental study is presented to evaluate the performance of the proposed approach; and finally, results and discussions are presented in the last section.

Artificial bee colony algorithm

Artificial bee colony (ABC) algorithm is an optimization algorithm based on the intelligent behavior of honey bees recently developed by Dervis Karaboga in 2005 [16]. In the ABC algorithm, the colony of artificial bees is composed of three groups of bees: employed, onlooker, and scouts bees. The first half of the colony consists of employed bees and the second half of onlookers. An onlooker bee is the one waiting on the dance area for making a decision of choosing a food source. Each food source is represented by an employed bee. Once a food source is exhausted, the employed and onlooker bees become a scout bee.

Basically, the ABC algorithm consists of three steps:

1. sending the employed bees into the food sources and evaluate their nectar amounts
2. selecting the food sources by the onlooker bees after sharing the information of employed bees

3. determining the scout bees and sending them into possible food sources

Mathematically, in the ABC algorithm a food source corresponds to a possible solution of an optimization problem and the nectar amount represents the fitness function of the solution. The number of employed bees or onlooker bees represents the number of solutions in the population (SP). At the beginning, a random initial solution is generated in the ABC algorithm with SP solutions (food sources positions). Each solution is a D-dimensional vector x_i (i=1,2,…,D), where D is the number of optimization variables in the problem. The population of solutions is subject to iterative cycles, C=1,2,…,Cmax, of the search processes of the employed, onlooker, and scout bees. A new solution (new food source) is generated when an employed or onlooker bee produces probabilistically a variation in the current food position (current solution) for finding a new food source (new solution). If the nectar amount (fitness function value) of the new food source is higher than the old one, then the bee memorizes the new food position and forgets the previous one. Once the search process done by the employed bees is completed, they share the nectar amount and position of the food sources with the onlooker bees on the dance area. Then, the onlooker bees evaluate the information and selects a food source depending on a probability value associated with that food source, p_i, which is computed by,

$$p_i = \frac{fit_i}{\sum_{n=1}^{SP} fit_n} \tag{1}$$

Where fit_i is the fitness value of the solution *i* evaluated by its employed bee; in other words, it is the nectar amount of the food source in the position i. SP represents the number of food sources which is equal to the number of employed bees (BP). A new solution is produced when probabilistically a modification in the current solution is performed; thus, a new possible solution is generated by,

$$v_{ij} = x_{ij} + \emptyset_{ij}(x_{ij} - x_{kj}) \tag{2}$$

Where $k \in \{1,2,\ldots, BP)$ and $j \in \{1,2,\ldots,D)$ are randomly chosen indexes; *k* index has to be different from *i* $\emptyset_{ij}$. is a random number between [-1,1]. When a food source is abandoned by the employed bees, this is replaced with a new food source randomly generated by the scouts. In the ABC algorithm, if a food source position cannot be improved after a fixed number of cycles named *limit*, then that food source is abandoned.

In general, in the ABC algorithm there are three control parameters used: the number of food sources, value of *limit*, and the maximum number of cycles.

Proposed approach

Injection molding is a dynamic manufacturing process where machine settings are fixed. Optimal process parameter setting requires of high computational analysis such as Finite Element (FE) analysis models, or very accurate prediction models [9]. The aim of this study was the development of a hybrid Artificial Neural Network-Artificial Bee Colony approach for the optimization of warpage in injection molding by coupling Finite Element (FE) analysis and artificial intelligent schemes. Computationally, FE models require a lot of effort and are not suitable for a large of repetitive analyses which are frequently necessary in an optimization algorithm. Therefore, a prediction model based on Artificial Neural Networks (ANNs) was employed for their ability to learn and map the complex nonlinear relationship between process parameters and warpage of molded parts. Consequently, Artificial Bee Colony (ABC) algorithm was used to optimize the process parameters with the fitness function based on the ANN predictive model. In order that the designed neural network obtains the ability of prediction; first, it had to be trained by a number of input-output data pairs. These input-output pairs were retrieved by a series of simulations in the FE analysis software Moldflow. Figure 1 shows a graphical representation of the hybrid ANN-ABC approach.

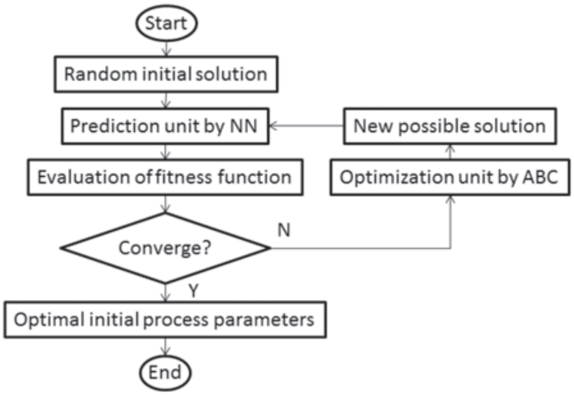

Figure 1 Hybrid ANN-ABC

First, a random food source (solution) is generated. Then, such solution is introduced to the neural predictive model to evaluate the fitness function. Subsequently, the optimization unit is used to find the optimal combination of process parameters within a predefined search space that will minimize warpage. Basically, the hybrid ANN-ABC approach consists of a prediction unit and an optimization unit.

The following section presents an experimental case to evaluate and validate the optimization approach.

Experimental study

The commercial software Moldflow was employed to simulate the injection molding process in order to retrieve the required samples to train the neural network, and to validate the proposed optimization method. A real plastic component was used to demonstrate the efficiency and validity of the ANN-ABC approach. Figure 2 shows the plastic part employed in the study under Moldflow environment. During the experimental study, an Arburg injection molding machine was used to simulate the process; table 1 shows the technical details of the machine. Table 2 shows the properties of the material used in the study. Alloy-steel (P-20) was used as mold material. Five process parameters were selected as design variables in the mathematical model. These variables are melt temperature (Melt_T), mold temperature (Mold_T), packing pressure (Pack_P), packing time (Pack_t), and cooling time (Cool_t).

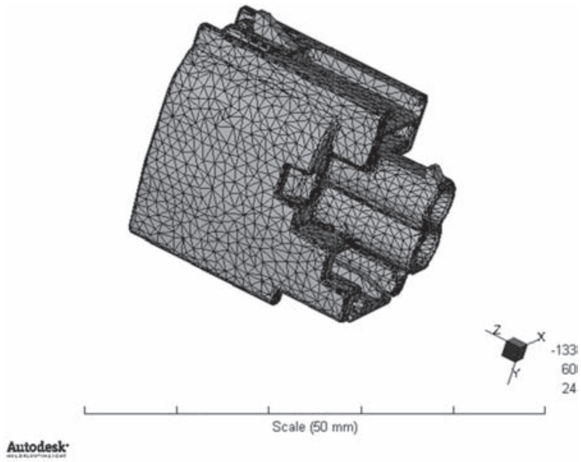

Figure 2 Plastic component

Table 1 Technical details IM machine

Manufacturer	***Arburg***
Trade name	Allrounder 220S 17 tons 1.3 oz (18mm)
Maximum machine injection stroke	55.58 mm
Maximum machine injection rate	32cm^3/s
Machine screw diameter	18 mm
Maximum machine injection pressure	250 Mpa
Maximum machine clamp force	17 ton

Table 2 Material properties

Family name	***Polyamides***
Trade name	Zytel 70G35HSLRA4BK267
Melt density	1.223 g/cm^3
Solid density	1.4369 g/cm^3
Ejection temperature	206°C
Maximum shear stress	0.5 MPa
Maximum shear rate	60,000 1/s
Elastic modulus	9120 MPa
Poissons ratio	0.4
Shear modulus	2750 MPa

Artificial neural network design

A 5-12-12-1 feedforward neural network was developed to create an approximate mathematical model between the process parameters and warpage of the plastic component. The aim of this mathematical model was to predict the warpage when different process parameters were introduced to the network. The structure of the designed network is shown in figure 3.

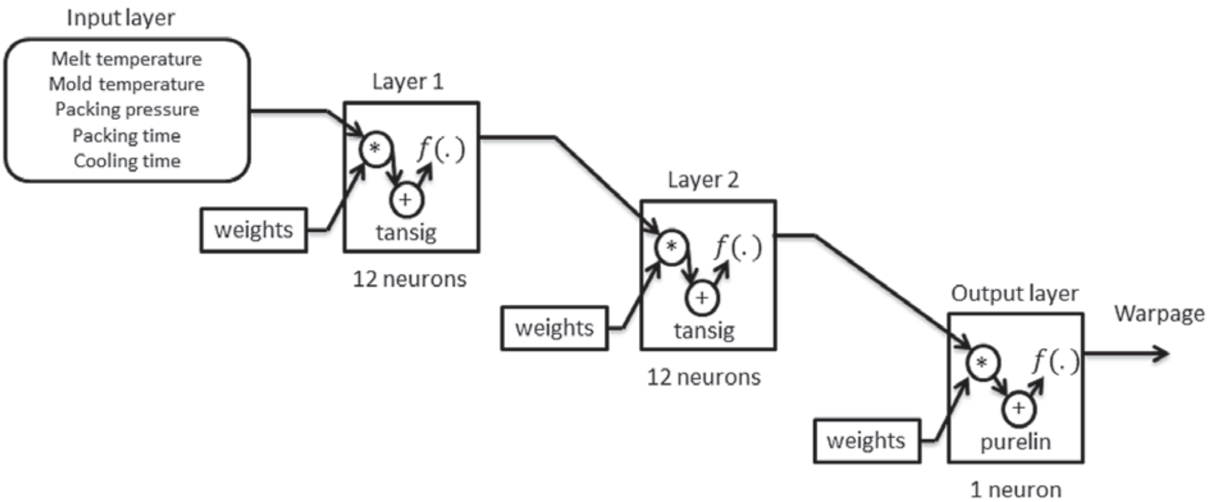

Figure 3 Structure of the designed neural network

Before the designed neural network can be used for prediction, it had to be trained properly. A number of input-output pairs were obtained from the FE analysis software Moldflow. Thirty two samples designed by the methodology of Design of experiments (DOE) were obtained as well as other 57 randomly generated. The obtained samples were divided into a training set and a test set, respectively. Figure 4 shows the different warpage values used in the training set, while figure 5 shows a set of nine input-output pairs (not used in the training process) used to test the precision of the network. All input-output data pairs were normalized within the range -1 to 1.

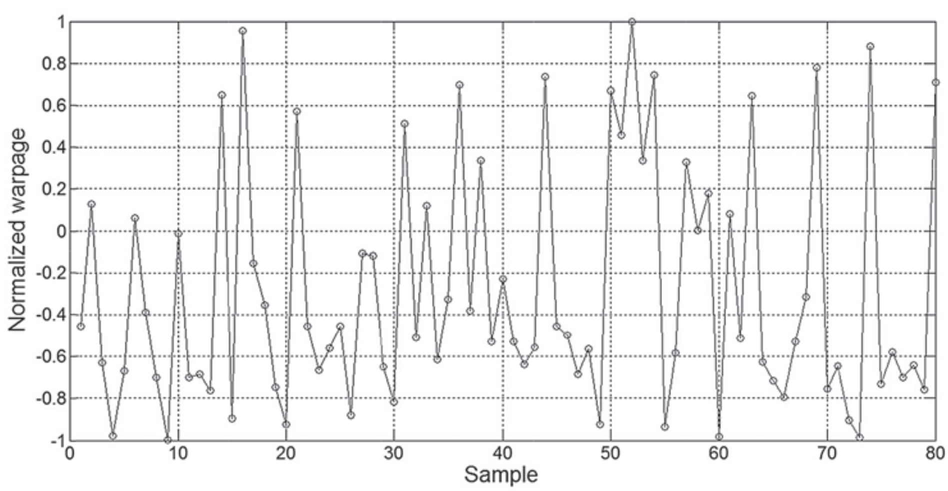

Figure 4 Warpage sample set

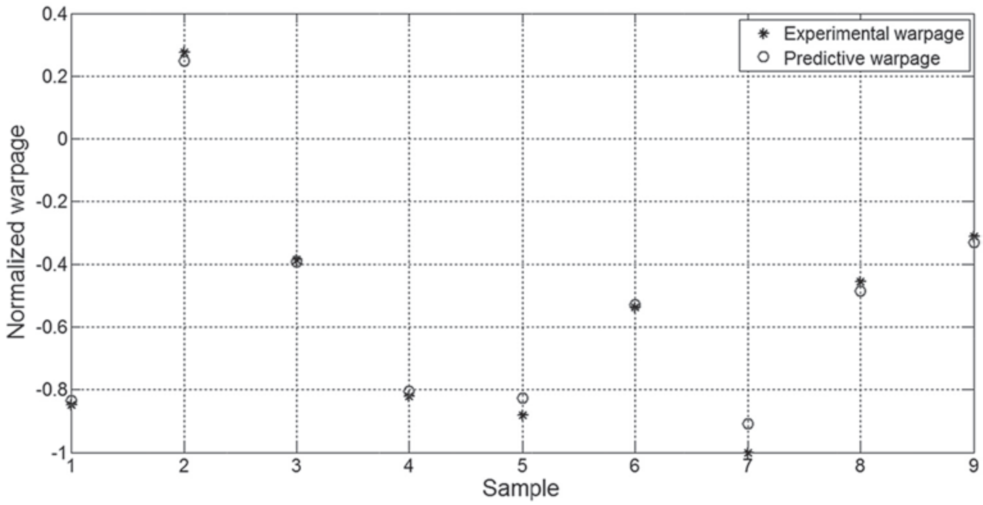

Figure 5 Testing designed neural network

Backpropagation algorithm was used to train the designed neural network. The learning rule was based on the Levenberg-Marquardt algorithm and the performance index was the mean square error (MSE). The training process after 10,000 iterations converged to an error of 1.194e-07.

The trained neural network was tested to prove the prediction ability using nine input-output pairs which were not used in the training process. The results were then compared with those obtained from Moldflow and are shown in figure 5. It is observed from the results that the prediction unit is in good agreement with the Moldflow experimental values. Prediction error was around 5% on average; therefore, the designed neural network was employed as an approximate mathematical function in the optimization problem.

Optimization with ABC

During the ABC optimization process, a food source (possible solution) was represented by using a five-dimension vector in the form

X = [Melt_T, Mold_T, Pack_P, Pack_t, Cool_t]

where each one of the design variables represents a process parameter. The mathematical model of the optimization problem was defined as follows:

Find X = [Melt_T, Mold_T, Pack_P, Pack_t, Cool_t]

Minimize WARPAGE

Subject to:

$250 \leq \text{Melt\_T} \leq 350$

$75 \leq \text{Mold\_T} \leq 125$

$5 \leq \text{Pack\_P} \leq 30$

$5.5 \leq \text{Pack\_t} \leq 7$

$3.1 \leq \text{Cool\_t} \leq 3.8$

where the objective function was approximated by the designed neural network and the search space is specified for each one of the process parameters. The control parameters considered of the ABC algorithm were the colony size, limit for scout, and maximum number of cycles. The colony size was fixed to 20; thus, the number of food sources was equal to 10. The limit for scout was fixed to 24, and the number of cycles equals to 10,000. About 30 runs were carried out using these algorithm parameters where for each run it was obtained the best food source (solution) with the best objection function value. Subsequently, from the different runs, a mean value was obtained for each process parameter, and it was set as the optimal initial value.

Results and discussion

The optimal initial process parameters for injection molding obtained from the hybrid ANN-ABC approach are shown in table 3 and were set on the Moldflow software to obtain the warpage value of the plastic component. Besides, in order to validate and compare the optimal results, it was obtained the warpage value of the part by setting the Moldflow recommended values.

Table 3 Optimal results obtained from ANN-ABC

	Melt temperature (°C)	*Mold temperature (°C)*	*Packing pressure (MPa)*	*Packing time (s)*	*Cooling time (s)*	*Warpage (mm)*
Hybrid ANN-ABC	257	86	30	6.6	3.4	0.2149
Moldflow recommended	296	109	24	6.3	3.5	0.2338

It is observed from table 3 that the optimized warpage value was 0.2149 mm. The normalized value of the optimized warpage was -1.08 which indicates this value was less than any other value used during the training or testing stages. Likewise, the normalized value of the warpage obtained from the Moldflow recommended process parameters was -0.53. It is seen from this comparison there was a significant improvement in the warpage value of the plastic component. The methodology is presented with the aim that can be used under different circumstances such as different materials, machines, or design of a plastic part. There are plenty of numerical optimization algorithms that could solve the above optimization problem. Artificial bee colony algorithm has emerged in the last years as an alternative option to solve fast and efficiently multivariable and multimodal optimization problems such as injection molding.

Conclusions

This paper presented a hybrid of artificial neural networks and artificial bee colony algorithm for finding the optimal initial process parameters for injection molding in order to minimize warpage in a plastic component. Neural networks were employed to approximate the complex relationship between the process parameters and warpage of a plastic part. Next, artificial bee colony algorithm was implemented to find the optimal set of process parameters that minimizes warpage based on the predictive results generated by the neural network model. The proposed approach is an alternative methodology that can be used to find the optimal set of initial parameters. In order to validate the presented scheme, an experimental case was presented by using finite element analysis software Moldflow. Results revealed the hybrid approach can efficiently support engineers to determine the optimal process parameters and achieve competitive advantages in terms of quality and costs.

Further research will focus on different surrogate models and by considering other design variables related to machine settings and mold conditions. Furthermore, multiple outputs have to be taken into consideration.

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