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Optimisation of injection moulded parts by using ANN-PSO approach

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Analysis and modelling

ABSTRACT

Purpose: The aim of the work was the optimization of injection molded product warpage by using an integrated environment.

Design/methodology/approach: The approach implemented took advantages of the Finite Element (FE) Analysis to simulate component fabrication and investigate the main causes of defects. A FE model was initially designed and then reinforced by integrating Artificial Neural Network to predict main filling and packing results and Particle Swarm Approach to optimize injection molding process parameters automatically.

Findings: This research has confirmed that the evaluation of the FE simulation results through the Artificial Neural Network system was an efficient method for the assessment of the influence of process parameter variation on part manufacturability, suggesting possible adjustments to improve part quality.

Research limitations/implications: Future researches will be addressed to the extension of analysis to large thin components and different classes of materials with the aim to improve the proposed approach.

Originality/value: The originality of the work was related to the possibility of analyzing component fabrication at the design stage and use results in the manufacturing stage. In this way, design, fabrication and process control were strictly links.

Keywords: Injection Molding; Finite element method; Artificial Neural Network; Particle Swarm Optimization

1. Introduction

Thermoplastic injection molding is a well-know process for manufacturing simple and complex shaped products in short time and at low cost. The fabrication cycle consists of three main phases, necessary to fill the mould cavity with molten polymer (injection step), add material to achieve the final part weight (packing step), drop polymer temperature to the ambient temperature (cooling phase). Mold opening and part ejection complete the process. All these steps are strictly related and several factors, such as material characteristics, molding machine features, part and mold design, processing parameters, influence the quality of final parts in terms of product appearance and strength [0]. The warpage and shrinkage of injection molded parts were extensively investigated by using numerical and experimental techniques. From the literature survey of the last years, the main approaches employed to investigate and optimize process conditions were the Design of Experiment and the Artificial Neural Network.

Design of Experiment (DOE) is a structured and organized method to determine relationships between factors affecting a process and output of the process itself. DOE techniques statistically quantify indeterminate measurements of factors and their interactions by observing forced changes made methodically. The main advantages of DOE techniques are the identification of the principal factors affecting the part quality and the improvement of the optimal solution search by removing factors with very low influence. The main limitations of the DOE methods are the difficulty to identify the process parameters set optimizing multiple objective functions and the choice of appropriate parameter ranges in which the relations between inputs and response are linear. In addition, historic data, available from previous experimental runs, cannot be included in the analysis. The Taguchi orthogonal array and the Response Surface are two of the principal DOE approaches applied in analysis of injection molding. These approaches employ a rectangular input space in each section plane of a multi-dimensional space to avoid risky extrapolation and randomized replications executed at each test point to assess process sensitivity. The Taguchi method optimizes design parameters to minimize variation before optimizing design to hit mean target values for output parameters. This method was extensively used to identify main factors affecting the part warpage and shrinkage on a flat plates [[1],[2]], box shaped parts [[3]] and real components [[4]]. One of the main outcomes reported from these studies was the identification of the packing pressure as the most important factor affecting the part quality. Research results also pointed out that the shrinkage of crystalline polymers mainly depended by the packing pressure while the melt and mould temperatures become more important in shrinkage of amorphous polymers. The Response Surface Method (RSM) was employed when the problem objective was the optimization of the process parameters. RSM was used to develop a statistically precise predictive knowledge about part warpage and shrinkage by using simple polynomial models between injection molding process parameters. The warpage reduction was achieved also optimizing filling and packing steps. The studies were performed on flat plates [[5]] and real components [[6],[7]].

An Artificial Neural Network (ANN) is inspired by the way biological nervous systems process information. The important element of this approach is the information framework of the processing system that encompasses a large number of highly interconnected processing elements (neurons) working together to solve the assigned problem. An ANN is designed for the specific application through a learning process adapting the synaptic connections between neurons. The approach processes information through a mapping mechanism in which the network evolves towards to a steady structure minimizing the errors between real and predicted responses on presented input-output pattern data. The input space may be non-rectangular and historic data can be used. More than one output is normally produced. The main advantages of ANN is the creation of relations between input and output data for not well known relations and/or too complex functions to be represented. In addition, the adaptive learning (capability to learn tasks based on the given data for training or initial experience) and self-organization (organization of the information received during learning time) are two important features of this approach useful to speed-up data structure creation. The main limitations of ANN are: (i) the sensitivity of the quality and type of data and pre-processing operations before dare are presented to the learning procedure and (ii) the interpretation of the results because rules used to obtain them are not completely intelligible. The ANN approach applied to injection molding field was used to identify main processing parameters affecting product quality of thin parts [[8]], determine the initial process parameters for box-and complex-shaped products [[9]] and predict the quality of complex-shaped injected parts [[10]]. These researches pointed out the potentials of ANN in predicting filling and packing conditions of injection molding parts without quantitative evaluating the influence of each process parameters on the final shrinkage of the part. The optimization was normally performed directly from the analysis of the results or by using other subsequent methods (e.g. Fuzzy Logic).

The aim of the present work was the optimization of the product warpage by integrating an Artificial Neural Network (ANN) predicting main filling and packing results and a Particle Swarm Optimization (PSO) to optimize the process parameters automatically. The Finite Element simulation and experimental validation were also performed on a real industrial component to couple with ANN-GA framework.

2. Particle Swarm Optimization

Evolutionary computation exploit a set of potential solutions, named population, and detect the optimal ones through cooperation and competition among the individuals of the population. Particle Swarm Optimization (PSO) is one of the population-based stochastic optimization technique inspired by social behavior of bird flocking [[11]]. PSO shares many similarities with evolutionary computation techniques such as Genetic Algorithms (GA). A population of random individuals is initially generated and these individuals probe the search space during their evolution to identify the optimal solution. Compared to GA, PSO does not employed evolution operators such as crossover and mutation and does not need information about the objective function gradient. Other advantages characterized PSO such as the easy implementation and the low requirement of computational resources.

In PSO, the individuals, called particles, are collected into a swarm and fly through the problem space by following the optima particles. Each individual has a memory, remembering the best position of the search space it has ever visited. In particular, particle remembers the best position among those it has visited, referred to as *pbest*, and the best position by its neighbors [[12]]. There are two versions for keeping the neighbors best position, namely *lbest* and *gbest*. The first (*lbest*) is related to the best position of the particle in the neighbors of the particle itself while *gbest* reefers to the best position recorded by the entire swarm. Each individual of the population has an adaptable velocity (position change), according to which it moves in the search space. Thus, its movement is an aggregated acceleration towards its best previously visited position and towards the best individual of a topological neighborhood. Compared to GA, the information sharing mechanism of PSO is notably different. Chromosomes share information and the entire population evolves towards an optimal area in compact manner. The evolution of particles, guided only by the best solution, tend to be regulated by behavior of the neighbors . In the simplest form, the position p and velocity v of each particle are represented by the following equations by considering *lbest* rather than *gbest* as the best position of the particle referred to the neighbors:

$$p^{n+1} = p^n + v^{n+1} \tag{1}$$

$$v^{n+1} = v^n + c_1 r_1 \left(pbest - p^n\right) + c_2 r_2 \left(lbest - p^n\right) \tag{2}$$

where c_1 and c_2 represent the acceleration terms and r_1 and r_2 are two random numbers, representing the individuality and sociality of one particle with the others. The velocity equation can be written in similar forms to the previous formulation in order to improve the converge by adding a weighting factor on previous velocity value and/or biasing the c-terms [[13],[14]].

3. Proposed Approach

For complex interactions between process parameters of injection molding, analytical studies are possible only for simple products. A numerical methodology is very useful to evaluate components with complex geometries but it is computational expensive if the aim is the optimization of the product performances. The objective of the proposed approach was the development of an integrated environment for the optimization of product warpage by coupling Finite Element and Artificial Intelligent approaches. In this way, the Finite Element (FE) Method allowed the deep investigation of filling and packing conditions on a reduced set of process parameters, the Artificial Neural Network enlarged the search space by predicting results on points different from those of numerical simulations and the PSO was involved in the optimization stage. Fig. 1 shows the flowchart of the proposed approach with three layers associated to simulation, prediction and optimization. The definition of these three layers was important to reduce the computational time. In fact, the direct link between the simulation software and PSO required a long time before optima were identified. The insertion of the prediction layer allowed the decoupling of simulation and optimization stages by inserting a ANN as result predictor.

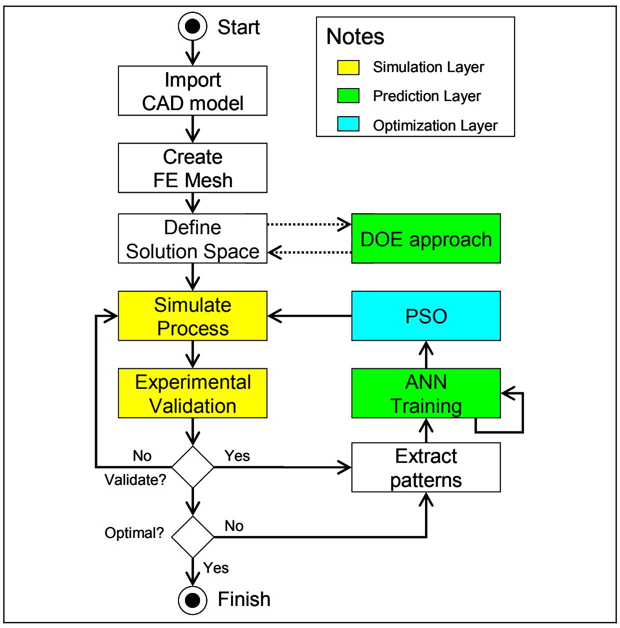

Fig. 1: Flowchart

Analyzing the flowchart in more detail, several sub-stages were defined. The CAD model of the product was initially imported and converted into a FE mesh. Element dimensions and number was carefully defined to achieve reliable results in reasonable time. The definition of mesh density was thus very crucial. A coarse mesh could behave to convergence solution problems and/or inaccurate results. On the contrary, a very fine mesh could lead to analysis costs in computing time out of proportion respect to obtained results. For this reason, some attempts were performed until a good compromise between result accuracy and simulation time was achieved.

Once the FE mesh was set, the solution space was defined. Three possible approaches were taken into account. In the first approach, a regular solution space equal to that obtained with a 2^n Full Factorial technique was defined. In this way, the influence of each process parameter on selected responses was evaluated and the solution space was better refined. The disadvantage of this approach was the possibility of detecting non-linear relations between factors and one single response, obtaining a low regression value. The second approach considered an initial solution set in which process parameters were randomly distributed. The advantage of this approach was the definition of a solution space in which regions leading to unfeasible solutions were avoided. The limit of this approach was the impossibility of evaluating the influence of process parameters on responses. The third approach consisted into the fusion of the above approaches, inheriting their advantages.

Numerical simulations were performed on defined solution space and main response variables evaluated. Experimental tests were also carried out to validate the FE model and tune FE parameters. If validation was negative, the simulation process was repeated until simulation results were able to predict experimental data. The input-output pattern were then extracted and sent to ANN. A feed-forward neural network was used to recognize and predict these patterns. The solution set was divided into training and validation sub-sets. The training data was used for the learning process of the network while validation set was used to verify if the network carried-out reliable forecasts in points different to those belonging to the training sub-set. The learning process was completed when Mean-Square Errors between existing data and predicted data on training and validation sets were below a defined threshold.

The PSO directly performed computation on ANN data to identify the optimal solutions. The particles were associated to the process parameters while the fitness function was a combination of the response variables. The particle encoding was performed by using integer number to respect the problem formulation. In fact, response variables had shown a low sensitivity to too small variations of the process parameters. The PSO was tuned by setting a small number of particles with low level of interactions between neighbors. A high particle velocity was initially set in order to efficiently explorer the solution space, avoiding local mina.

4. Application to a real component

The proposed approach was applied to a real industrial component to verify potentials and limitations. The product, a cover of an electric assembly, was characterized by a box-shape with internal ribs and was made of Ultramid B3S (un-reinforced PA6 material) of BASF Company. Material properties are reported in Table 1.

Fig. 2-A shows the product features. The main product dimensions were 45.00·25.50·16.270 mm^3 (total volume to be filled equal to 7.22·10^3 mm^3).

Table 1.
Material properties.

Melt\Solid Densities (g/cm^3)	0.92-1.13
Water Absorption (%)	9.5
Linear Mold Shrinkage (cm/cm)	0.01
Melt Flow (g/10 min)	147
Min-Max Melt Temperatures (°C)	250-270
Maximum Shear Stress (MPa)	0.5

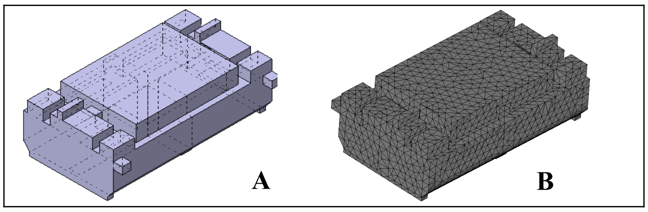

Fig. 2. Product and FE Mesh

This component was chosen as case study to test the proposed approach because two explicit objectives were required to be satisfied such as the warpage reduction and a short fabrication cycle time. The presence of sections with dissimilar thickness, and the need of assembling the electric part inside made the satisfaction of the two goals difficult to solve.

4.1. Finite Element Model

The products was manufacturing by using a four cavity mould. Only one cavity was modeled with the commercial software MOLDFLOW MPI version 5.1. The FE mesh consisted of about 5,500 element triangles and 2,800 nodes with the fusion (double-skin) representation (Fig. 2-B). The mean aspect ration of the triangles was equal to 1.7. The feeding system consisted of one sprue, main and secondary runners and sub-marine gates. Because the symmetrical flow paths occurred, only one cavity and a partition of the feeding system were modeled while the other mold regions were referenced in the analysis by occurrence numbers. Identical flow paths have symmetrical physical geometries and identical volumes of plastic flowing through them. For this reason, the attribute *Occurrence*, the value of which was equal to 4, was applied to this mesh in order to simplify the amount of modeling required for a flow analysis by specifying the number of times that a given flow path was repeated. This model simplification was also applied to runners and gates but not for the sprue that was a common region to all four cavities.

4.2. Definition of the Solution Space

The main process parameters chosen for the analysis were the mod temperature *TM*, the polymer molten temperature *TI*, the flow rate *Q* and the hydraulic packing pressure *P*. The parameter ranges, reported in Table 2, were chosen according to material specification suggested from the plastic manufacturer.

Table 2.
Process parameter ranges.

	Min	Max
Mold Temperature *TM* (°C)	40	80
Melt Temperature *TI* (°C)	250	270
Flow Rate *Q* (10^3·mm^3/s)	10	80
Packing Pressure *P* (MPa)	25	40

The packing and net cooling times were set equal to 6 s and 10 s respectively. The packing time values was regulated to avoid premature (the gate freeze before the part was completely filled) and tardily gate freezing (the gate froze before the part causing under-packing effect). The net cooling time is the time after the pressure phase and before the part is ejected from the mold. The net cooling value was chosen in order achieve 80% of the complete solidification of the part before ejection. The filling/packing switch was equal to 92% by volume filled.

The solution space consisted of 16 sets created by permuting the minimum and maximum values of the process parameters plus 1 central set with the mean values plus 10 sets randomly generated. The entire solution space covered all vertexes of the process parameter space and allowed the 2^4 Full Factorial to be performed. The random sets inside the solution space above defined allowed the ANN to be efficiently trained.

4.3. Simulation results and experimental validation

The numerical simulations of part filling and packing were performed. The main response variables were the average volumetric shrinkage *VS*, the end of fill *EF*, the maximum shear stress at wall *SS*, the average bulk temperature *BT* ad the final part weight *W*. *SET1*=(*TM*=40°C, *TI*=250°C, *Q*=10·10^3·mm^3/s, P=*25*MPa) and *SET2*=(*TM*=80°C, *TI*=270°C, *Q*=80·10^3·mm^3/s, P=*40*MPa), containing the maximum and minimum values of the process parameters, were chosen to experimentally validate FE results. Table 3 reports response variable results of the two sets, where average bulk temperature is substituted from its difference with the melt temperature. The high values of *ΔBT* and *SS* (the maximum *SS* allowed for the polymer was 0.50 MPa) of *SET1* were justified by the fact that the parameters were too near the zone of the incomplete filling (short shot) in the process window. On the contrary, a high volumetric shrinkage value was obtained with parameters of *SET2*.

Table 3.
Simulation Results

	SET1	SET2
Avg. Volumetric Shrinkage *VS* (%)	4.47	6.22
End of Fill *EF* (s)	5.63	0.52
Shear Stress *SS* (MPa)	0.69	0.48
Avg. Diff. Bulk Temp. *ΔBT* (°C)	-39.9	1.60
Final Part Weight *W* (g)	38.95	38.20

Product fabrication was performed with a DEMAG Concept 810-370/80 hydraulic injection molding machine. The process was stabilized with 10 cycles prior to each run and then 5 consecutive shots were collected and labeled from each set.

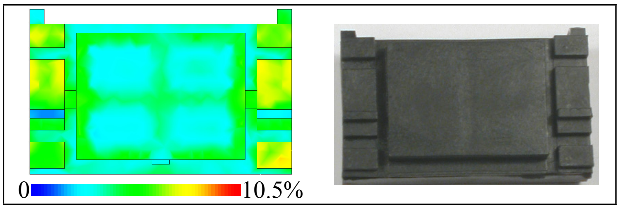

Fig. 3. FE and Experimental Vol. Shrinkage (*SET1*)

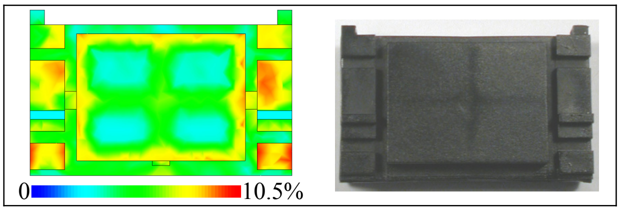

Fig. 4. FE and Experimental Vol. Shrinkage (*SET2*)

Fig. 3 and 4 report the FE predictions and manufactured components with process parameters of *SET1* and *SET2*. The specimen obtained with *SET1* parameters was characterized by a low surface finishing because of the high flow rate. However, the volumetric shrinkage was low. On the contrary, a high volumetric shrinkage occurred for the specimen with *SET2* process parameters and the surface finishing was fine. A good agreement between numerical and experimental results was achieved, confirming the capability of the FE model to well substitute the experimental fabrication. The validation was also carried-out by comparing the predicted and real linear shrinkages of the products manufactured with the two process parameter sets. The displacements of the numerical model were evaluated by using the flow induced residual stresses while the real displacements were acquired by using a 3D Coordinate Measuring Machine with a Renishaw touch probe. Fig. 5 shows the main dimensions measured from both numerical and experimental specimens while Fig. 6 reports comparison between numerical (*SETxnum*) and experimental (*SETxexp*) measurements for the two sets. The results were in agreements also for this analysis.

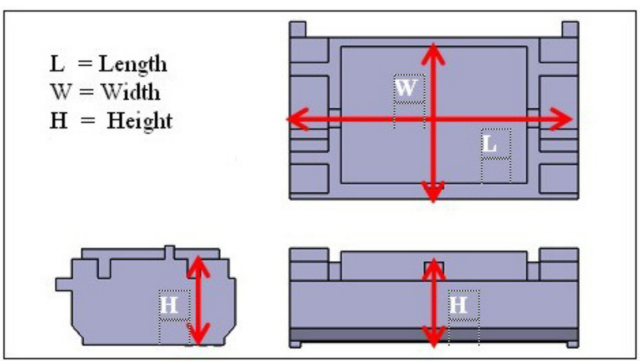

Fig. 5. Main dimensions for measurements

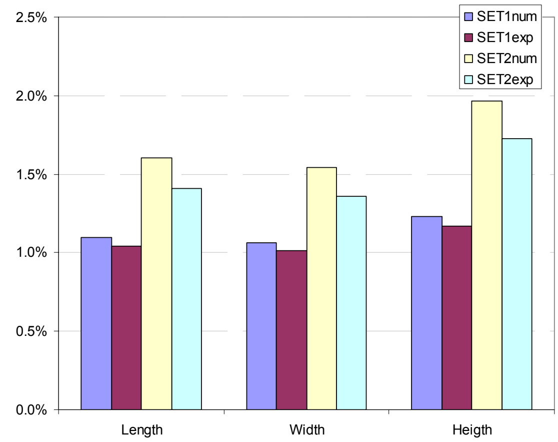

Fig. 6. Num. and exp. measurements (units mm/mm)

An additional verification was performed by comparing the final weight of each manufactured part with that attained with FE simulation. The direct measure of specimen weight was performed with a KERN EW 220-3 NM precision balance immediately after component ejection. This operative condition was very important to respect because the water absorption of the material was very high (9.5%). The average weight of the 20 components (4 parts for each shot) per space point was evaluated. The mean difference between the numerical and experimental weight was about 1-2%.

4.4. Artificial Neural Network Design

The significant factors and the coefficient of determination R^2 of the 2^4 Full Factorial extracted from the entire solution space is reported in Table 4. The 1st and 2nd order model to response data were evaluated.

Table 4.
ANOVA

	Factors	R^2 - 1st order
Avg. Volumetric Shrinkage *VS*	*TM,Q,TI,P*	96%
End of Fill *EF*	*Q,P*	97%
Shear Stress *SS*	*Q,TI*	59%
Avg. Diff. Bulk Temp. ΔBT	*Q*	60%
Final Part Weight *W*	*TM,Q,TI,P*	96%

The values of R^2 of the 1st order model were high *VS*, *EF* and *W* responses but low for *SS* and ΔBT. The R^2 of these last responses did not greatly incremented with the 2nd order model. Thus interactions between factors were ignored.

The ANN was designed to create more precise relations process and response variables that those of the Full Factorial design. The proposed ANN was a supervised multi-layer feed-forward one with 4 input (process parameters *TM*, *TI*, *Q* and *P*), 10 hidden and 5 output (response variables *VS*, *EF*, *SS*, *ΔBT* and *W*) neurons. The layer transfer functions were the pure-line (input-hidden layer) and the saturation-line (hidden-output layer). The learning rule was based on the Levenberg-Marquardt algorithm while the performance function was the Mean Square Error (*MSE*) minimization of the network errors on the training set [[15]]. The learning procedure of the ANN was performed on the training set values using an iterative procedure, ending when the mean R^2 between predicted values and pattern data was greater than 95% and the *MSE* value on the training set was lower than 10^{-5}. The validation set was needed to compare the ANN response with FE solver results to verify and adjust the ANN mapping. Fig. 7 shows the performance *MSE* of the ANN for the training and validation sets. The mean of the R^2 values of all responses was equal to 98%. The *MSE* value of the validation set remained constant after the 2nd epoch.

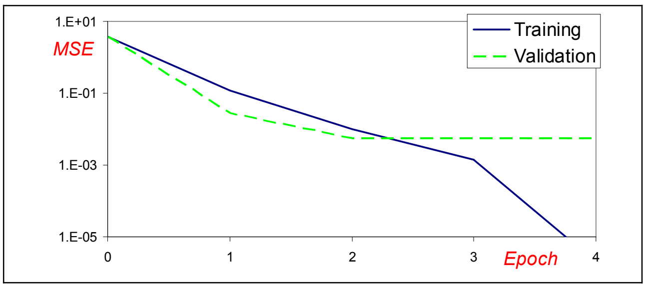

Fig. 7. ANN Training

4.5. Optimization with PSO

The particle was represented by suing a four-dimension vector in the form

$$p = [\,TM,\ TI,\ Q,\ P\,] \quad (3)$$

containing the main decision variables. Each particle was a candidate solution when it was inside the solution space. The initial swarm consisted of 40 randomly initialized particles and their velocities belonged the range (-10,+10). The acceleration constants c_1 and c_2 were both equal to +1 while random values r_1 and r_2 were chosen in the range (0,+5) and converted into integer numbers. The maximum number of iterations was equal to 100. At each iteration the best fitness of the particle (*lbest*) and best fitness of the swarm (*gbest*) were recorded.

The fitness function *FIN* was the sum of the un-coded response variables *VS*, *SS* and *ΔBT* :

$$FIT = VS + EF + \exp(-\Delta BT)^2 + PEN \quad (4)$$

In addition, a penalty factor *PEN* was added to avoid that particles went outside the solution space. Its maximum value was equal to +5. The choice of this fitness function form was linked to the objective of minimizing not only the volumetric shrinkage *VS* but also the end of fill *EF* and the bulk temperature difference *ΔBT*. An additional constraint was imposed on the maximum value of the shear stress of the particle $(SS)_{particle}$ by:

$$(SS)_{particle} < SS_{MAX} \quad (5)$$

where SS_{MAX} was the maximum shear stress allowed.

Fig. 8 shows the convergence of the swarm during its evolution. The minimum value of the fitness function was attained after 75 iterations and remained stable until the maximum number of iterations was reached. All solutions were feasible and the convergence was very fast in the first 10 iterations. Sub-optimal solutions were also obtained the main differences of which were the value of *ΔBT*. The fitness of the optimal solution was -1.53. The values of process parameters (*SET*) and response variables are reported in Table 5.

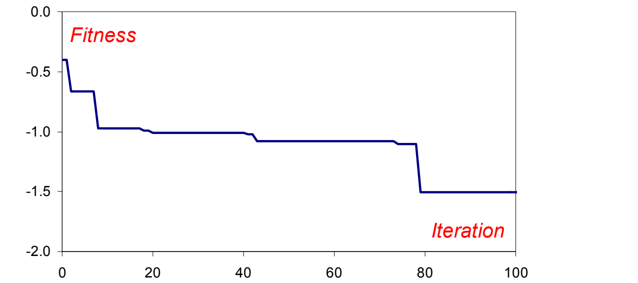

Fig. 8. PSO Fitness vs. Iterations

Table 5:
Optimal Solution

	SET
Mold Temperature *TM* (°C)	50
Melt Temperature *TI* (°C)	250
Flow Rate *Q* (10^3·mm^3/s)	73
Packing Pressure *P* (MPa)	40
Avg. Volumetric Shrinkage *VS* (%)	4.78
End of Fill *EF* (s)	0.59
Shear Stress *SS* (MPa)	0.49
Avg. Diff. Bulk Temp. *ΔBT* (°C)	-1.2
Final Part Weight *W* (g)	38.78

These values were in good agreement with the numerical simulation performed. Fig. 9 shows the comparison between volumetric shrinkages of the FE simulation and experimental fabrication of the component by using parameters of the optimal *SET*. Some interesting results were pointed-out. The average volumetric shrinkage was low and the volumetric shrinkage of the entire part was more uniform. In addition, the surface finishing was very good and the low value of end of fill *EF* guaranteed high production rate for the component.

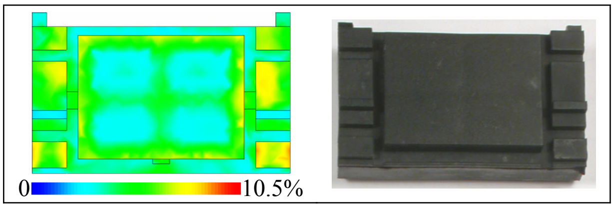

Fig. 9. FE and Experimental Vol. Shrinkage (*Opt. SET*)

5. Conclusions

This research has confirmed the efficiency of the integration between Finite Element and Artificial Intelligent methodologies to identify optimal parameters for the injection molding process. The evaluation of the FE simulation results through the Artificial Neural Network system was an efficient method for the assessment of the influence of process parameter variation on part manufacturability, suggesting possible adjustments to improve part quality. The proposed approach has operated on the variables of the injection molding phases in a very simple way, predicting the part quality. The proposed methodology has pointed out the potential of Particle Swam Optimization coupled to Artificial Neural Network in the optimization of the process parameters of the thermoplastic injection molding. The main advantages have been the reduction of volumetric shrinkage and filling of the part, with the possibility to automate optimization task. The results were confirmed from Finite Elements simulations and real fabrication of the investigated component.

Future researches will be addressed to the extension of analysis to large thin components and different classes of materials with the aim to improve the proposed approach. The method will be implemented by considering other variables, related to machine characteristics and/or working conditions. The Artificial Intelligence system will be improved to evaluate historical data, updating the training set with new experimental data and knowledge.

Acknowledgements

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