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INTELLIGENT SYSTEM TO SUPPORT MICRO INJECTION PROCESS THROUGH ARTIFICIAL INTELLIGENT TECHNIQUES AND CAE MODEL INTEGRATION.

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ABSTRACT

At present, the need to produce micro plastic parts has increased considerably due to the progress that technological devices have made and the desire to make them smaller and with a greater number of features. Although the production of these parts has advanced widely, manufacturing methods and techniques are still very complex, which means longer production times and consumption of raw materials, generating great possibilities of failures in the final product.

In this project a propose of integration of CAE Modeling and artificial intelligence systems to support the process in the production of micro plastic parts is presented. Based on analysis provided by CAE systems, studies will be carried out for a large number of diverse parts, searching a first look at the behavior of the injection plastic process. Making use of image processing systems a primary database will be created, with shape parameters and variables such as temperature, injection time, closing pressure, shear rate and number of deformations on the different parts.

With neural networks and the database created, intelligent system will be trained for the recognition of variables that are handled and thus identify the optimal form and injection parameters that affect the quality of the part. Fuzzy logic will be control ranges of variables that affect the parts in order to give recommendations that intervene in the manufacturing process, and be able to obtain results with a smaller amount of deformations.

Through the generation of recommendations, the manufacture of plastic parts from optimal values can be carried out. Artificial vision is used to analyzes the failures presented on the manufactory process, in order to execute a new data interaction on neural network and fuzzy logic system, in such a way that a new analysis and new cycle of injection can carry out. With each new injection cycle the system is trained, analyzing the presented deformations to reach a point where the recommendations help to produce a part without failures and industrial quality. Through the tests, an injection cycle reduction of approximately 39% was achieved, which means a lower consumption of material and production times, giving better system efficiency over conventional processes. This process is proposed for a large number of micro-parts, searching that the system can give recommendations to almost any type of geometric shape.

Keywords: Micro-parts, Microfabrication, CAE systems, Expert Systems, Shape Variables, Process Variables, Fuzzy Logic, Neural Network.

1. INTRODUCTION

In the search for knowledge and technological progress, the humanity wants to optimize processes and machinery in a way to make more accessible and suitable for the general public. In today's society, marked by the use of technology in every aspect of daily life [1], people must think of objects that are easy to manipulate and that fulfill broad tasks, meaning that these are small objects capable of carrying out various actions and improving life aspects.

Thanks to the information age [2] is possible to perform various actions with just one hand movement. The instruments used to perform different actions in new technological devices must have high precision and operating capacity. The micro-parts, being such small and highly precise components, allow all the activities of devices in an effective way, but for make all this possible, the manufacturing process has to be very complex.

Taking into account the need for production of millimeter and micrometric parts, different manufacturing techniques based on material molding, extraction and injection have arisen [14], but many of these are based on the experience of the operator, who must be an expert in the control of process parameters that affect geometric and material variables [15]: in addition, if such methods are to be applied in the manufacture of millimeter and/or micrometric scale parts, precision in variable manipulation must be high, which in turn increases production times, as well as materials.

In the micro-manufacture [3] of plastic parts are involved several operating variables, these affect many subroutines that must be made to obtain the desired part, from the design of molds, the machining techniques (that must be highly precise) and the microinjection (that must be constantly controlled). To make all processes involved possible is necessary to invest too much time in tests and manufacturing controls. Taking into account the importance of micro-parts today and the complexity of their manufacture, uses intelligent systems is the best way to facilitate production processes and thus reduce time and loss of material, making use of the technologies such as process automation and expert systems.

The total controls of the operators on the production processes must be intervened by expert systems, these must have the ability to control and identify faults and irregularities that may occur during the manufacturing process [4]. The control of variables such as temperature, application pressure, flow of material, among others, search to reduce the possibility of defects such as deformations and reflows on the material. Defects, in many cases, make necessary external interventions on the parts, making that these losing quality and competitiveness in the market. The dependence of the operators must be considerably reduced, especially in the micro-manufacturing processes. When an operator handling such precise measurements is so difficult to control the involve parameters, which results on inferiority and inability of micro parts to comply with the necessary standards and functions. Fuzzy logic systems allow managing qualitative functions in parts, based on process rules compliance [5]. Process rules are already established by operators and operating manuals, so [6] fuzzy machines would serve as a support system for operators and process control [7], to reducing defects in the injection molding process [8].

Fuzzy Logic is a multivalued logic that allows representing mathematically uncertainty and vagueness, providing formal tools for treatment, this attempts to model the ambiguity of belonging with which a variable is perceived, where an element does not belong entirely to absolute truth. Fuzzy logic is based on fuzzy sets, in the same way that classical set theory is the basis for Boolean logic. With fuzzy sets, logical statements of the yes-then type are made, defining these with Fuzzy Logic. Fuzzy sets are defined by an added membership function, defined as a real number between 0 and 1. The concept of a fuzzy set or subset is associated with a certain linguistic value, defined by a word or linguistic label where this is the name of the set or subset [13].

Like other expert system, neural networks are more complex systems based on interactions and training [9], which can synthesize large numbers of parameters from different learning techniques and predict the real behavior of the system, achieving values close to system operation. Neural networks are more used by the Ability to learn to perform tasks based on training or initial experience (Adaptive Learning), also by the capacity of creating his own organization or representation of the information, it receives through a learning stage (Self-organization). A special quality of Neural networks is a fault tolerance where, though partial destruction of a network leads to a degradation of its structure, some network capabilities can be retained, even suffering great damage [10]. In a complex system, neural networks can operate in real-time. Machines and systems with special hardware and software are designed and manufactured to obtain the capacity to performed neural computations in parallel [11]. Whit the facility of insertion into existing technology, specialized chips can be obtained for neural networks that improve their ability in certain tasks, facilitating modular integration into existing systems [12].

A system that allows the integration of simulator analyses, gives control of options on the parameters to obtains better results in the real manufacturing phase, analyses the critical variables such as filling time, material temperature, mold temperature is necessary [16]. This kind of systems must be developed to analyses the variables that interview in the process like ejection temperature, maximum injection pressure, geometric characteristics, manufacturing time, inlet flow, closing force, holding pressure, injection volume, pressure maintenance time, mold pre-cooling time and cooling time of the part [17]. Plastic injection processes simulators allow obtaining an overview of the behavior that occurs during manufacturing processes [18]. These facilitating the controls on the parameters involved in the production of parts [19].

Applying technique of expert systems in microinjection processes, makes possible to carry out a complete analysis of the parameters that affect the system, these establishing the appropriate behavior to obtain a part without defects. Expert systems, aside from serving as support to process optimization, give real and indicated values for the desired part, granting more control tools to the operator, and therefore decreasing the load and the dependence that is generated.

The use of simulators in plastic injection processes allows to obtain an overview of the behavior that can occur during the manufacturing processes, facilitating the controls on the parameters that intervene in the micro-fabrication of parts. A system should be considered that allows to integrate the analyzes obtained in the simulations to give control options on the parameters and obtain better results in the actual manufacturing phase, analyzing variables such as temperature, pressure, geometry, vertices, manufacturing time, flow of input, closing force, among other variables that intervene in the final results.

This project seeks the integration of CAE Modeling and artificial intelligence systems to support the process in the production of micro plastic parts from the design and development of software, which allows to give control recommendations both in the form and in the process variables that affect the manufacture of the micro-parts. It is proposed to collect the data that feed the system through the analysis of the results that the CAE simulation studies provide, in order to create a primary database with the expert systems can perform interactions and promote recommendations on the variables that affect the process. Each new injection cycle generates new variables of form and process that feed the system, with the aim of generating a more complex learning and thus obtain better results in a fewer number of cycles. The software is intended to be functional for a wide variety of geometries, so that it can be used for almost any type of micro-part.

2. PROBLEM STATEMENT

The micro-parts refer to all the components of a micrometric scale and that are currently required in multiple technological environments such as bioengineering, micro-electronics, automotive, biomedicine, among others [3]. Being such complex components, require a large number of manufacturing parameters to meet the quality standards into compliance with their work. These parameters are related to mold variables, material variables, shape variables and process variables.

Although the manufacturing processes of various parts of plastic have been studied for many years, the great diversity of geometries and materials that can be used in processes often hinder the results, increasing materials and production times. In the elaboration of the micro-parts, involved processes usually become difficult since to the need of a greater precision in the dimensions, these require systems of control, quality and accuracy, and in many occasions, it is necessary to print more than once the part that is desired obtain.

In the current injection processes, the operator is who has the decision on manufacturing parameters [6], which makes the manufacture of plastic parts is completely empirical, in addition, the operators must be expert staff with specific skills, which generates him a high control over the quality standards with the part will work.

In the development of parts with micrometric characteristics, the manufacturing processes require unconventional designs that allow the systems to maintain the mechanical characteristics and at the same time have an industrial quality index. In order to produce these parts is necessary to invest a lot of time in geometric mold designs and in the adjustment of the control parameters, on many occasions these production and design times can be from weeks or months until reaching an optimal design and control [4].

Thanks to the latest technological advances in the various branches of artificial intelligence, expert systems techniques, 3D printing, among others, the ability to optimize the processes of control and manipulation of parameters has been demonstrated. In the manufacture of micro plastic parts, the use of these technologies helps to optimize processes giving better results in the production of high quality parts.

In the phases that involve micro-manufacturing processes, pre-processing phases are taken into account, such as the geometric design, the design of the mold, the manufacture of this, among others. The manufacture of the mold in the elaboration of the micro-part of plastic is key to obtain results that can be competitive in the market [5]. Consideration should be given to materials that are capable of withstanding high temperatures and the pressure applied so that the plastic part obtains the desired characteristics and can fulfill its function.

From the above, two questions are generated that allow to frame and direct the research.

- Which variables of the manufacturing process of micro-parts of plastics should be controlled and taken into account to design an intelligent system?

- Which artificial intelligence technologies and expert systems are the most suitable to use in each of the phases of production of micro plastic parts in order to support the productivity of the process?

3. OBJECTIVES

3.1 GENERAL OBJECTIVE

Design a system that integrates CAE models and analysis with artificial intelligence techniques, in order to support the micro-manufacturing processes of plastics parts.

3.2 SPECIFIC OBJECTIVES

- Design models of micro plastic parts with different geometric characteristic that allow to generalize of analysis and definition of geometric parameter requirements.
- Analyze the influence of geometry, material and machine variables in the formation of micro plastic parts using CAE model systems.
- Identify the variables that affect the formation of the micro plastic parts through rapid prototyping tests of different parts.
- Design an artificial intelligence system throw the identification of injection defects on micro-plastics parts give recommendations of optimal values parameters.
- Integrate CAE model systems with the Artificial Intelligent System developed in order to reduce and validated the injection cycles required to produce a good quality injection part.

4. CONCEPTUAL FRAMEWORK

The development and progress that humanity has undergone in recent decades has been influenced by the search for digitalization and miniaturization of the components of daily life, in order to improve the quality of life of human beings [2]. This progress has been greatly influenced by the evolution of microelectromechanical systems (SMEM).

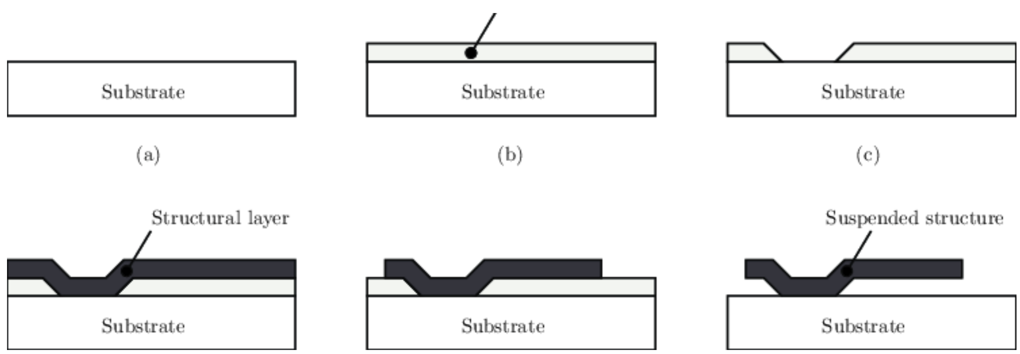
The SMEM are microelectromechanical systems able to carry out different tasks, these works thanks to the interaction between the micro-electro-mechanical parts. Mechanical and electro-mechanical elements of different physical dimensions that can vary from a micrometer (one millionth of a meter) to one millimeter (one thousandth of a meter) [3].

Over the years, several techniques have been created to manufacture micro-parts from simple processes such as micro-mechanized to some more complex such as ultrasound molding. Next, what processes that have originated and what each of them consists of will be specified [27].

4.1 SMEM MANUFACTURING PROCESSES

4.1.1 Micro-machining in volume. Technique by which structures inside a substrate are produced by selective and anisotropic attacks [24]. This process consists in the application of material on engravings, generally on the underside of the substrate, in mechanical structures in order to create a part of free contact. The material can be applied in materials such as glass, gallium arsenide and silicon. This type of micro-machining requires a large amount of material for both the injection and the mold as it practically crosses almost the entire mold wafer. For this process anisotropic or isotropic attacks of volume of almost all the depth of the substrate are carried out [28].

Figure 1. Schematic of the volume micro-machining process.

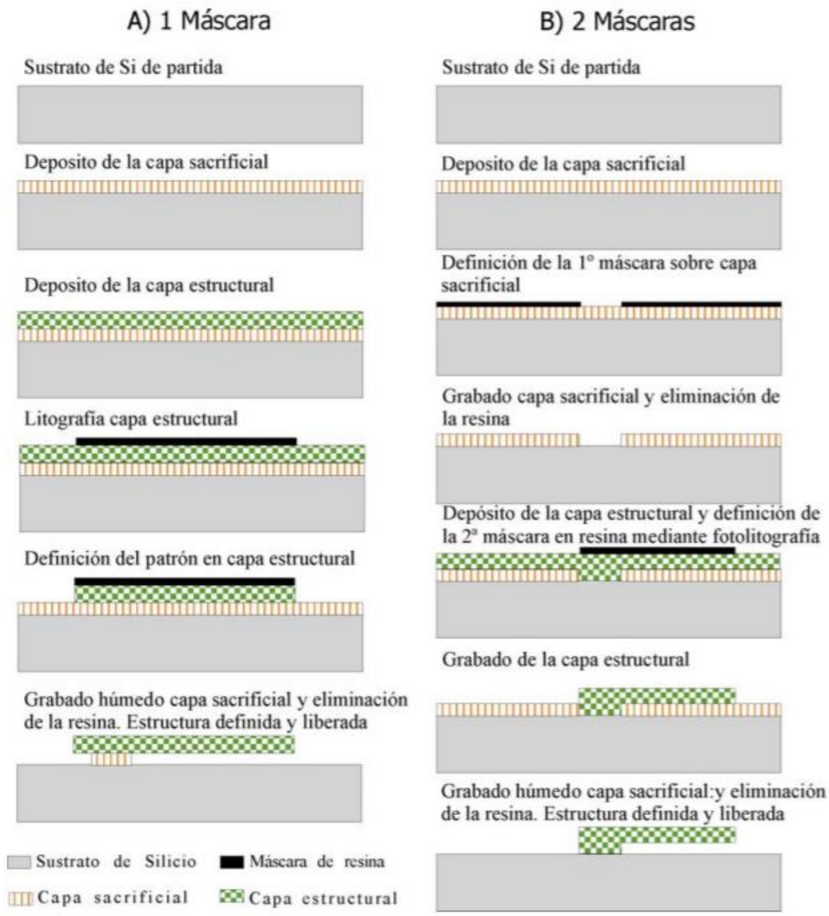


Source: https://www.researchgate.net/figure/Typical-steps-in-a-surface-micromachining-process-a-substrate-preparationtypically-a_fig5_221912642

With the development of technologies of engravings by reactive ions has been possible to implement dry attacks, which allows to control the attack speed, the depth and the verticality of the same [25].

4.1.2 Micro-machining surface. The surface micro-machining is based on the construction of the structure through of layer-on-layer deposition on the starting substrate. Each of the masks defines the shape of the structural layer, the first layer is defined as sacrificial layer since it will be removed later, and on this initiates the structural layer that will give shape to the micro-structure. The structure pattern is defined on this layer. Finally, the sacrificial layer is removed and the structure is released [28].

Figure 2. Schematic of the surface micro-machining process.



Source:www.tdx.cat/bitstream/handle/10803/5347/mvg1de3.pdf?sequence=1&isallowed=y

4.1.3 LIGA and Micro-molding. LIGA (Lithographic Galvanic process, Electrodeposition and Molding), lithography is defined as the technique used to engrave a pattern on a solid surface. The most common case used is the application of X-ray lithography on a conductive substrate coated with PMMA (highly transparent thermoplastic polymer). Once the engraving is done, the filling of the engraving with metal (Aluminum) is applied by electrodeposition in order to obtain a mold that will serve to make a ceramic sintering or a plastic replica [28]. Other lithography techniques vary depending on the resolution and the desired wavelength. (See Table 1).

Table 1. Achievable resolution of different lithographic techniques.

Technical characteristics		**Resolution**	**Wavelengtha**
Mercury lamp	Line G	400 nm	436 nm
	Line I	300 nm	365 nm
Laser	KrF	180 nm	248 nm
	ArF	100 nm	193 nm
	F_2	70 nm	157 nm
Lithography of Immersion		35 nm	193 nm
Extreme Ultra Violet		45 nm	13 nm

Source: Clealand-03, ITRS-04.

4.1.4 Laser beam machining (LBM). The use of laser technology in micro fabrication processes allows intermediate precision in addition to offering tools in the processes of cutting, welding, drilling and marking. The biggest advantage that it offers over other types of micro-manufacturing is the reduction of the areas affected by heat and therefore the reduction on the mechanical loads applied to the structure [28]. This type of micro-part manufacturing is usually applied in materials such as metals, ceramics, glasses and polymers. Normally these require very short wavelengths as they seek greater precision, for this, the lasers that are currently used are of the excimer type that offers a micrometer precision or solid state lasers multiplied in frequency that are limited to an accuracy of tenths of micrometers.

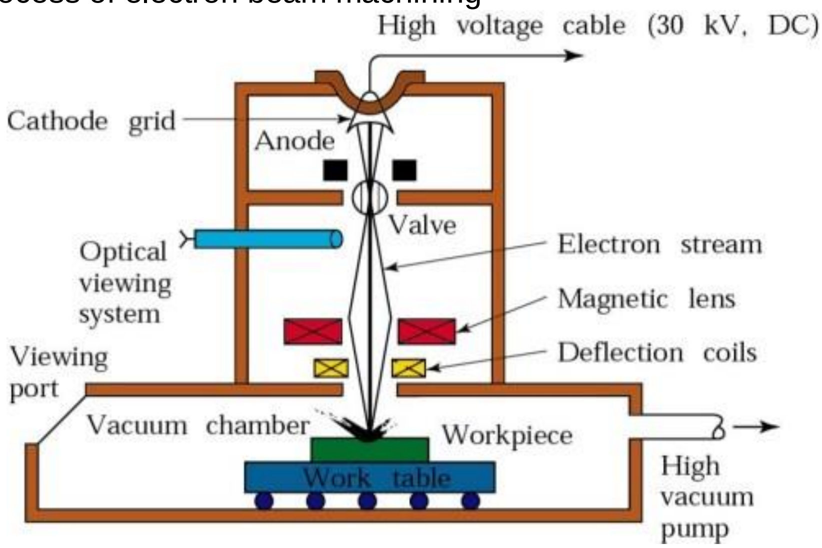
4.1.5 Micro-EDM (Micro EDM). The electro-erosion process consists in the generation of an electric arc between an electrode and a part that through of a dielectric removes material until the shape of the electrode is reproduced. In this process it is necessary to use conductive materials so that the formation of the electric arc can be established, which causes the detachment of the excess material from the part. The biggest difficulty in this process is its speed, since it is a relatively slow process that is used in the formation of non-conventional geometries of hard and brittle metals [28]. The most used electro-erosion methods are:

- Penetration EDM.
- Wire EDM.
- Drilling EDM (or rectification EDM).

In the last 45 years, different methods have been developed, although the most used are still electro-erosion by penetration and wire EDM.

4.1.6 Electron beam machining. In this process, a beam of focused electrons is used at high speed that melts and eliminates the excess material to give shape to the desired part. The process starts in a vacuum chamber when a tungsten filament produces a beam with 3000 watts that is directed to the part to be machined, with the help of electromagnetic fields and coils which allow to focus and melt the material in a controlled manner. It is mainly used to create surface variations on the micro-part. The electron beam comprises a diameter between 10 mm and 200 mm, and a high energy intensity that allows crossing large thicknesses of material (up to 65 mm approximately) [28]. This process is highly used due to the manufacturing speed, the energy efficiency it provides when using the light beam and the high quality indexes on the part, although it is limited by the size of the vacuum chamber, so the dimensions of the part will depend directly on the size of the camera, besides that it is not possible to produce large volumes of parts.

Figure 3. Process of electron beam machining



Source: https://basicmechanicalengineering.com/electron-beam-machining-ebm-principles/

4.1.7 Machining by ultrasound. Ultrasonic impact grinding consists of the use of vibrations on the machining tool, which when vibrating at a low amplitude (25 to 100 microns) and at a high frequency (15 to 30 kHz) removes material to a specific shape. The tool penetrates the part in an abrasive medium under controlled conditions, allowing operations such as cuts of small holes, slots or intricate patterns [28]. This method to generate a very fragile rupture is mainly used in materials such as glass, ceramics, silicon or graphite.

4.1.8 Microinjection. The injection process starts from the entry of the material into pellets into a hopper that takes the material to a cylinder with a screw in which heat is supplied to it to transform its solid state into a visco-ceramic state that allows it to flow into the mold through of the injection pressure, in which the material solidifies and takes the shape of the mold.

In this process more than 200 variables intervene that normally must be changed according to the quality of the parts produced (injection defects more than 30 completely qualitative), through an expert operator who by his experience defines which process parameter should change and in what intensity, change that makes at the foot of the machine [28]. This phase of the process, in which the machine has to be tuned for each of the micro-parts, can last for days, weeks and even months, until finally it is possible to obtain micro-parts with the necessary quality and precision. Taking into account that this phase must be repeated each time a part is changed in each machine, and that the results of the same geometry are different on different occasions, the complexity of the process is very high and the productivity is low.

Knowing the great diversity of existing processes and the complexity of each of these, the need to use intelligent systems that can solve a multivariable system in a short time and that reduce the dependence of the process on an expert operator becomes more evident.

4.2 INTELLIGENT SYSTEMS

Intelligent systems refer to a set of tools and applications that combine characteristics and behavior similar to that of human or animal intelligence and with which it is able to collect, extract and order information collected from different sources for the sole purpose of creating intelligent media and artificial for various uses. These are usually used for support and decision making.

For a system to be considered intelligent, it must have several functionalities among them [16]:

4.2.1 Intelligence. In artificial intelligence, intelligence is assigned to the ability to achieve the objectives in decision making through the perception and flexibility of development in their environment. Normally the term intelligence is applied to a machine when it is capable of imitating the cognitive functions that human beings associate with mental processing such as learning or solving problems. Intelligence can also be defined as the ability of a system to interpret the data of the surrounding environment, in order to learn from these data and achieve tasks and objectives through the flexible adaptation of what has been learned [29].

4.2.2 Systematization. The systematization refers to the ability to form a system, so is the specific organization of various elements that are part of something. Each of the parts of the system have a relationship with each other, which are governed by a set of rules, methods or data, which in turn is a form of classification. When systematization is attributed to a system, it refers to the ability to be part of a universe, with a limited extent, which forms a correlation between other parts of the system that can be more or less strong among themselves.

4.2.3 Objective. An objective is the end to which it is desired to arrive, for a system the fulfillment of the objective is the one that drives the system, and from which it leaves for the taking of decisions. Normally there are many levels of objectives with which the system works, must focus on compliance with these from the analysis of their environment and the collection of data that allow you to make decisions that approximate the ideal behavior. Since there are main objectives and sub-objectives the system usually seeks to fulfill mainly the objectives that have more weight and allow to develop the main objective.

4.2.4 Sensory capacity. The system's senses are the parts that can identify environmental variables (sensors). The system starts from the received signals in order to learn and interact with the environment in the process of making decisions, normally these signals are identified as electrical impulses that come from the capture of ultrasound signals, humidity, speed, temperature, light radiation, contact or sound that are in the middle of the system [29].

4.2.5 Conceptualization. All thinking starts from a concept, so the ability to interrelate each of the concepts in order to obtain a meaning between them implies the development of different levels of abstraction. This is one of the most complex processes that a system can have since the storage of different variables that define the concept as such require a large storage and processing capacity, in addition to having many subsystems that allow to interrelate each one of the variables to give an end and a sense to what is being worked on.

4.2.6 Rules of action. The rules of action are attributed more to the fuzzy logic. It is the interpretation of the memory itself to the data collected previously and with which a learning process has been developed, to a situation that starts from the analysis of the environment and the fulfillment of the objective is a decision and therefore an action that generates a consequence with which the system can learn for a future decision making (feedback).

4.2.7 Memory. Memory, as already mentioned, is the storage of variables, concepts, and rules of action that instruct the system, this includes the experience of the system that allows it to improve in decision making. It is necessary for some occasions to apply the filters of classification of experiences since on many occasions the system can give negative results and it can not classify them properly, the reason why it must have the correct control over this [29].

4.2.8 Learning. Learning can be considered as the most important capacity of the system since it is from this that it can make decisions. All the information received from the environment, the rules of action, the fixation of abstract concepts and the interrelation between these are part of the learning of this, and it is for all those that the system can make the best decision for the best development of the objectives [29].

4.3 ARTIFICIAL INTELLIGENCE TECHNIQUES

Artificial intelligence techniques refer to the learning, reasoning and prediction processes that systems use to perform a task. These techniques may depend on pre-programmed parameters, learning systems, reasoning according to pre-established values or cases, data interaction processes in order to arrive at an established model, among others. On many occasions, these methods work together to arrive at a meaningful prediction that is related to the problem and the environment in which it is found.

4.3.1 Machine learning. Machine learning is system processes that use self-learning techniques to arrive at constructed knowledge. The self-learning process is achieved through programming processes in which deduction tasks are performed based on the interaction and relationship of cases or predefined values. Machine learning is widely used by various systems to perform prediction and control tasks (banking systems, traffic control) [30].

4.3.2 Fuzzy logic. Fuzzy logic refers to the process of analysis through compliance with rules, in which it is these that lead to a rational value. Fuzzy logic manages linguistic values close to those of the human being (more than, very, very), based on predefined values that allow the generation of value ranges and standardization to arrive at a term that fits the initial parameters, and which somehow fulfill a proximity value. Fuzzy logic is widely used to carry out adjustment processes, in which the approximation to a value allows giving a more accepted answer [31].

4.3.3 Expert systems. Expert systems refer to systems that specialize in developing a specific area. Through programming, database, environment reading and predictive development, expert systems can develop specific tasks, giving correct answers on problems that are generated in their field of application. Expert systems are used in specialized processes, where a repetition of tasks and analysis of these are necessary [32].

4.3.4 Data mining. Data mining is the process of extracting information from a large database. Data mining seeks to establish sets and patterns of behavior among a large amount of data and established values, through the interaction and relationship of values and sets that allow reaching a behavioral model and generating responses. This technique is widely used for classification processes, where a large amount of data must be classified and related to lead to a response [33].

4.3.5 Bayesian networks. Bayesian Networks are an analysis process that, through of the data relation (graph), seeks to infer an influence of value and arrive at a certain value. Bayesian networks are used as methods of influencing relationships, where the values are related to each other to determine a set of interrelations that complements and has a meaning. Bayesian networks seek to establish patterns of behavior that manage to define a model of behavior and generate new values that are attributed to new knowledge [34].

4.3.6 Neuronal Networks. Neural networks are a set of learning techniques that seek to establish relationships between a large amount of data to generate new knowledge. Neural networks seek to establish behavior similar to neurons in the human brain, where the transport and interaction of information from neurons allows a new result to be generated; In neural networks, a data interaction between nodes known as neurons is established, the interaction between nodes can generate new values and sets that are interrelated. Through the interrelation of data, new information is generated that is adjusted to the determined values. Neural networks are one of the most complex systems used in artificial intelligence since allows you to generate relationships and values from various data without a pre-established relationship [35].

4.3.7 Reactive systems. Reactive systems are those that perform tasks in real-time through analysis of the environment. The reactive systems are used as analysis systems, which through of sensors can study the environment in which they are found to generate an adequate response. Reactive systems process and react through various programming systems in which these are related depending on the information acquired [36].

4.3.8 Rule-based systems. Rules-based systems are analysis processes to generate a result by complying with pre-established rules. These systems adjust to the environment through the acquisition of information, which, when related to already programmed parameters, adjust to compliance with an established rule that leads to compliance with an action. Rule-based systems are used in controlled environments to fulfill repetitive tasks that do not contradict their own programming [37].

4.3.9 Case-based reasoning. Case-based reasoning is a process in which, by analyzing past experiences, a task can be carried out. This process is based on the analysis of past information; By which this performs analyzes of similar experiences that allow analyzing how to generate a new result. Case-based reasoning is very similar to the learning system used by human beings, in which through experiences they analyze similar situations to make a decision [38].

4.3.10 Semantic networks. Semantic networks are part of computational linguistics, which through programming, seeks to emulate linguistic reasoning. This type of network seeks to relate definitions and concepts so that new knowledge can be generated. Systems based on semantic networks are very close to the language used by humans, so these are so used as relationship systems to search and generate new information [39].

5. THEORETICAL FRAMEWORK

The development of the plastic micro-part begins with the use and application of the SMEM, from these was that the investigation and the manufacture of micrometric components began, capable of carrying out different activities.

5.1 HISTORY AND APPLICATION OF SMEM

The first record of production of a micro-part is given to the manufacture of the first contact point transistor [20] in the Bell laboratories. The transistor made with germanium average about half an inch thick and with this opened the possibility of construction of electrical parts with increasingly smaller semiconductor materials. Thanks to this development the piezo resistive effect of semiconductor materials was discovered in 1954 [21], such as silicon and germanium, which further impelled the development of SMEM since they allowed much better measurement that air or water pressure metals sensors.

Since 1954 the development of smaller components had not been exploited, the need to create micrometric transistors was left out, and it was not until 1958 when the first integrated circuit was created [22] that saw the need to create smaller components. During the 1960s and 1970s, various micrometric-scale electrical components were developed, including silicon transistors, the resonant gate transistor (RGT) developed by Westinghouse that functioned as a frequency filter for integrated circuits, micro-machining sensors of pressure with a silicon diaphragm developed by Kurt Peterson of the IBM research laboratories, these sensors could measure much better than other pressure sensors thanks to the thin membrane which allowed greater deformation.

In 1979 Hewlett-Packard was awarded the design of a printing alternative known as Thermal Inkjet Technology (TIJ), which consists of heating the ink and making it flow through micro-nozzles of high density that allowed a higher resolution in printing. In 1986 an atomic force microscope (AFM) was developed by IBM scientists, this device allowed to detect forces of the order piconewtons (pN) through a probe coupled to a lever of about 200 micrometers (μm), which could trace the topography of a nanometric sample, this invention was fundamental in the investigation of nanometric parts. Throughout the 1980s, great advances were made in SMEM technology, where the first electrostatic rotary motor [23] and the development of comb structures that move laterally to the surface (1989) stand out.

Starting in 1993, micro-manufacturing techniques are being promoted with the creation of a foundry by the North Carolina Microelectronics Center (MCNC) with the aim of creating more accessible and profitable systems and parts for a wide variety of products users. The production of accelerometers by Analog Devices was increasing which increases the availability and use of airbags in automobiles.

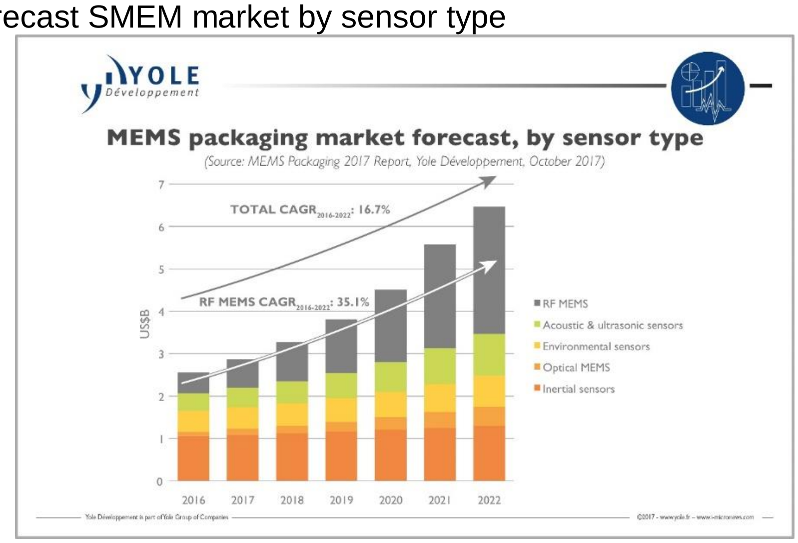
In medicine, great advances have also been made by SMEM with the creation of fully functional artificial organs, the use of microinjectors and micro-cameras that allow diagnosis of blood flow channels, the use of sensors that they allow to take control of cardiac states, among many others.

There are many types of SMEM that have been classified according to their application and use [3], they are generally divided into:

5.1.1 Classification of SMEM:

- Sensors: Electronic and mechanical devices used to measure from chemical, mechanical, thermal, optical and inertial variations. They usually transmit these values as electrical signals.
- Actuators: Devices that comply with the objective of generating a stimulus to other components, usually this stimulus can be mechanical, electrostatic or thermal.
- RF SMEM: Devices specially designed for the transmission of radio frequency signals, generally include antennas, switches and capacitors.
- Micro-Opto-Electro-Mechanical Systems (MOEMS): Optical function devices that allow to reflect, amplify direct or filter light spectra, are mainly used as reflectors or optical switches.
- SMEM for micro-fluids: Devices designed to handle small volumes of fluids, in general these are classified as micro-pumps and micro-valves.
- Bio-SMEM: Devices designed to interact specifically with biological samples. They are designed to interact with proteins, biological cells and medical reagents. They are normally used to supply medicines or perform medical tests.

Figure 4. Forecast SMEM market by sensor type



Source: *Yole Developpement*

The SMEM are involved in the development of many of the current technologies, not only medical, so their manufacturing process can vary. In the last decades, different types of manufacturing have been created such as Micro-Molding, 3D Printing, Laser Machining, Micro-Electro erosion, among others.

5.2 DEVELOPMENT AND IMPLEMENTATION OF SMEM TECHNOLOGIES

Research in micro-manufacturing of plastics has had a great development in recent years thanks to the progress and use that has been given to 3D printers from the integration of SLS systems and the creation of mass parts [40]. Although this technology exists since 1983 when the American physicist Chuck Hull creates the first part printed in 3D and creates stereolithographic and later in 1984 patented a method that allowed to obtain solid objects through of fine printing capable of hardening polymers with ultraviolet light [26], it was until 1987 when the first SLA type machine, developed by the company 3D Systems (3D Systems, Hull, Chuck 1987), was made that the relevance of this New process has in the methods of manufacturing parts.

Since the 90's have been investigating the utilities that these new processes can have in different branches of science, as an example you can take the creation of a fully functional 3D kidney with the ability to filter blood and produce dilute urine in an animal (wake forest institute for regenerative medicine, 2002), this process can be considered as one of the first fabrications of micro plastic parts, from there the search for applications of the manufacture of plastic parts by printing 3D has no end [41].

Into the last decade, different techniques have emerged for the manufacture of micro-parts that revolutionize the industry as it is known [42]. In 2016, the Technological Center of Catalonia manages to manufacture micro plastic parts by a method of molding using ultra sound that allows to create parts with a lot of precision (Eurecat, 2016), according to Xavier López Luján (Corporate and General Director of Operations of Eurecat.) "Sonorus 1G allows to mold with maximum precision micro-parts of plastic, some of them with geometries until now impossible to manufacture, improving, in addition, the energetic efficiency of the process very significantly and reducing the consumption of material" (López Luján, EARTO Innovation Awards 2016).

In the academic field, different injection positioning methods have been developed to optimally control and obtain results. One of these is based on the Bresenham algorithm, which allows controlling the movement between two points of the XY plane which guarantees trajectory tracking and error minimization [43]. At Kansas State University, a quality control system for the 3D printing process has been developed, through of a camera the part is evaluated during the printing process at various control points through of a computerized processing software. images and SVM (support-vector machines) allows to verify the quality of the part in real time which not only helps to eliminate the waste of material and time, but also avoids the need to reprint the whole part.

The control processes for the manufacture of micro-parts are diverse, from the complete control of an expert operator [4], to autonomous systems verified by positioning algorithms and fed by data capture sensors. Many of these processes can be controlled by artificial intelligence techniques and expert systems based on fuzzy logic (FL), these are software capable of making decisions from a knowledge base and making inferences similar to human ones, some such as systems experts based on case reasoning, fuzzy logic or neural networks [9]. These are a very useful tool to handle a large number of qualitative parts functions, without requiring a training phase. There are many applications for fuzzy machine controllers [7] or to reduce defects in the injection molding process [8]. They are also applied to correctly determine different injection parameters, such as the length of the flow [17], which has a great influence on the final quality of the injected part.

Some recent works use the Taguchi method to optimize injection molding parameters to reduce shrinkage [44]. Others use a gray diffuse system to design the optimal process for injection molded parts with a thin-shell feature [45]. Despite the success of such developments in the establishment of process parameters for specific cases, there is still a problem in how to use and adapt them in the case of injecting different parts, especially if it is the precision that must be had for the manufacture of micro-parts. In the last years, the industrial robotics has burst with force in applications of processes of manufacture that for a time were restricted to the cartesians machines, allowing the automation of processes like the milling and the polished. However, to obtain high dimensional and surface quality parts, special robots are required whose availability is limited due to their high cost [46].

The automation of processes of polishing of molds through of robots presents as difficulty that the robotic manipulator must carry out the process maintaining a constant force during the operation [6], which demands the realization of a trajectory of the robot with force control. This type of control is not immediately feasible in conventional commercial robots. Force control can be done in two ways, through passive control and active control [47]. In the passive control a mechanical system ensures that the abrasive tool remains in contact with the surface being worked by an elastic element. In these systems, the robot performs a pre-programmed and fixed trajectory and it is necessary to perform several tests until the operation begins to give the expected results, which involves a high cost in time of system preparation. The result is a not very flexible manufacturing system, in which any variation in the characteristics of the mold to be processed, will require taking measures to avoid a system failure, which does not have the intelligence to adapt to the new working condition. On the other hand, in active systems, sensors are used to measure the force and control the trajectory of the robot. Smart robotic polishing (with trajectory control by force) has been applied in various finishing operations of mechanical parts. Nagata [48] presented a system of robotized polishing of molds for the manufacture of plastic bottles that considers a final sanding tool that integrates a biaxial load cell to measure the polishing forces. The system is capable of positioning with an accuracy of one tenth of a millimeter. Current trends in industrial robotics demand efficient, flexible, and robust robots that possess a certain level of autonomy [49]. In this sense, industrial robotics has evolved towards robots with sensorization and security capabilities, which allow them to perform tasks that previously only a human being could perform. However, in spite of the great advances in robotics, it is necessary to emphasize that in order to make a robot autonomous and intelligent, it is always necessary to develop the knowledge that will later be implemented in the robot's control system.

In applications the micro-parts, mainly the SMEM [3] (microelectromechanical systems), have had great importance in the technological development, inertia sensors, gyroscopes, radio frequency systems, pressure sensors, are just some of the technologies that have had a great advance thanks to the manufacturing processes of micro-parts. The massive development of digital technologies has been greatly benefited by the possibility of creating increasingly smaller parts, the processors currently used have micrometric and even some nanometric characteristics, which makes them powerful electromechanical components. Another sample of SMEM that have had a significant development is in the electronic part, many sensors, actuators and controllers are now on a micrometric scale which allows to include more components in the devices, giving them greater capacity to perform different actions.

6. STATE OF THE ART

For the documentation of this work, searches for articles related to research-related topics such as:

- Micro injection by molding.
- plastic injection molding process.
- expert systems applied.
- CAE models applied.

A range of research was maintained for the last 10 years (2010 - 2020), where articles focused entirely on the microinjection processes of plastics were sought, in addition to the techniques and processes that may be involved to optimize the process.

The articles were classified according to the topics of interest of the project and focused on:

- Studies on the control of parameters in the plastic injection processes.
- Analysis studies of the microinjection process of plastics.
- Studies on the use of simulation tools applied to the microinjection processes of plastics.
- Studies of artificial intelligence systems applied to the microinjection processes of plastics.

Through experimentation has been determined that in every injection process, one of the main parts is the determination of the conditions of the control parameters that intervene in the process (pressure, mold temperature and ejection temperature). The research focused on flow behavior tests has been carried out to obtain the basic parameters of the material used (Polymers) and to make predictions of the flow behavior that the injection channels must have to fill the mold cavities completely [50]. In many injection processes, control techniques have been developed in order to allow taking data on the behavior of the tools.

Data such as the speed of the piston with respect to the injection time, the pressure exerted on the injection polymers, the filling time of the mold cavity and the position of the closing tools are one of the most used [51]. Various systems have been developed in order to improve the efficiency of the injection molding processes. Studies that have focused on the optimized design of molds with different characteristics such as cool the positions with thicker walls, have improved the temperature control process and the reduction of plastic defects [52].

The use of statistical methods to analyze the critical processes involved in injection molding has been one of the most studied branches, providing analysis of influence on applied controls, and the critical variables that are most involved with machine parameters [53]. Other processes involve online monitoring systems, which allow the processes to be analyzed and studied by various sensors that are transmitted to online networks that analyze and study production cycles, reporting and taking action on process control [54]. In conjunction with online processing techniques, the optimization of the injection processes has been developed, generating new optimization processes such as the use of digital image processing that allows generating relationships between variables and control parameters to arrive at an optimization model with system feedback [55].

The focus on the control of a single parameter such as temperature has generated various studies, in which they focus on the analysis and study of the influence of a single variable that alters the process in various ways and that can generate changes in the final results [56].

The study of the behavior of the polymers that are used in the injection processes (mainly in the microinjection) has a big impact on the final results. The investigation of polymeric materials generates new variations that must be taken into account during the manufacture of polymeric parts, in the same way, new techniques are generated that allow obtaining variable results on the behavior of the final parts [57].

The analysis of the quality of the components generated by the plastic injection processes plays a very important role when talking about process optimization. The optimization investigations look for an intermediate point between quality and production, so that the parts manufactured in the injection processes maintain quality indices that allow them to be functional in industrial processes, through the analysis of process behavior models [58].

The analysis of the physical and mechanical properties of the plastic materials used in the injection processes are critical to define the quality of the parts generated. The use of techniques such as fused deposition modeling allows to study characteristics of materials such as viscosity, density, and water absorption, which facilitate the selection of materials for each design [59].

The investigation of behavioral models focused on the process of microinjection of plastics has increased considerably in recent years. Like the microinjection of plastics be a critical process has been studied in different ways, looking for a model that allows improving the controls that are applied to the parameters involved in the process. The study of the injection processes in real time allows obtaining data that facilitates the understanding of the development of the process, and the generation of control techniques on them [60].

Analytical models such as the prediction of filling for micrometric parts have been developed in order to estimate suitable processing parameters for different product geometries [61]. Different investigations that focus on evaluating the most characteristic parameters involved in molding microinjection have been developed. It takes an evaluation approach to obtain algorithms and methodologies used in different models to improve industrial manufacturing processes, taking into account the problems and strengths that methodologies can have [62]. The investigation of the plastic properties that the materials have at the time of being injected is critical. Many investigations have focused on the analysis of the properties of materials and the parameters in the micro injection processes, classifying and giving values that allow to standardize controls on the variables and materials involved [63].

The deepening of research and experimentation in order to optimize microinjection processes has increased with the development of new methodologies and techniques. The design of experiments focused on the rapid manufacture of micro components has been studied in different fields. In the sought to design micro components that maintain quality and reliability restrictions have been decided to reduce the variety of changes in process parameters during operation, highlighting six parameters that influence the surface quality, flow length and the aspect ratio that are determined by statistical analysis for specific materials [64].

The use of statistical control analysis techniques such as the Taguchi method is also widely used for the behavior analysis of the parameters of the microinjection process. Most of the studies focus on the control of parameters such as barrel temperature, mold temperature, holding pressure and injection speed. Through the analysis of matrices obtained by experimentation and the study of data by the aforementioned techniques has been possible to understand the characteristics of the process parameters in terms of their main effects, interactions and sensitivity to noise and to adjust them for their optimal performance [65].

The analysis of the flow behavior in the microinjection process has been key to determine the models that are inherent in the process. In different investigations, the Phan-Thien-Tanner model (PTT) has been used to represent the rheological behavior of viscoelastic fluids, in combination with models of sliding limits and mathematical equations of pressure variation and fusion flow. Many of the models and their combinations have been taken to system codes to be solved by finite element techniques, allowing to predict the behavior of temperature, pressure and filling time in real processes [66].

The manufacture of molds in the microinjection processes is a critical part of the process since the final results depend on these. Due to this, studies focused on the analysis of the manufacturing of molds have been critical to improving the processes, such as the analysis of roughness and wettability that the polymers have when in contact with the wall of the molds and that affect the production and quality of the part injected [67]. Some studies have used chemical processes that allow improving efficiency in mold design processes. The use of blowing agents together with the molds allows to improve the release processes by creating separating layers between the polymers and the mold walls, reducing the presence of defects and imperfection in the final parts [68].

One of the biggest problems of using models applied with finite element techniques is the approach it has. Many of the computer systems developed to perform simulations are focused on conventional injection processes. When a simulating microinjection process is developed, the results are not the reality that can be presented in a real process, simulators do not have the ability to analyze the flow channels of micrometric scale that the systems have in real life and the result are very variables.

In recent years, analysis techniques focused on microinjection processes have been developed through meshing recommendations, the variation of ambient conditions and controls on the intervening control parameters that allow a more realistic approximation of the behavior of the process of microinjection [69]. Other methods applied to improve the precision of simulators in microinjection processes are focus on the analysis of the effect of pressure on viscosity and the effect of cavity deformation during molding. these methods are carried out on defined polymers to which the parameters of rheology and compression are known [70].

In the search for the optimization of the processes of plastic microinjection, simulators have been used in conjunction with data analysis to obtain an approach to the real behavior of the processes, in many cases, the manufacturing processes have been taken to the study of a specific element for which a whole system of study and behavior analysis is carried out [71]. The use of simulators in the injection processes has allowed to deepen in the analysis and study of the parameters that are involved in the processes, managing to improve the understanding and precision of the manufacturing methods, achieving better quality results [72].

Simulators uses to verify the filling process during the microinjection molding process has been studied in different ways. In recent articles, a multi-scale method is proposed where the conventional method with macro-scale factors is analyzed against the micro-scale method where takes slip and surface tension into account to investigate the filling of the micro cavity. Studies demonstrated that the use of this multiscale method allows obtaining very real simulation values compared to a real process [73].

The uses of CAE simulation systems are the most widely used in the analysis of microinjection processes, due to the multiple tools they use, which allows obtaining a first look at the behavior of the process through the variation of the control parameters. Various studies have used CAE tools for the analysis of the process, such as the study of the gate location in asymmetric multi-cavity injection molds, where training data were managed using CAE simulation tools to be analyzed by matrix study processes, resulting in optimization of gate location [74].

Through CAE analyzes, the development of new methods for selecting optimal values for the injection process has been investigated. The establishment of 3D data tables of the plastic parts in UG allows studying the optimal values of injection pressure, injection time, mold temperature, melting temperature, location of the gate and guide. In the same way, the investigation allows the optimization of the design of molds improving the quality of the molds, as well as reducing the cycle of development of the molds [75].

During the last years, the increase of intelligent systems capable of making decisions has had a greater use and development in different processes. Various investigations have focused on studying how the application of artificial intelligence systems can benefit the control of parameters that influence injection processes, highlighting the benefits that can be obtained from using these systems [76].

The design of molds has been one of the most studied aspects for the application of artificial intelligence techniques. The study of the mold surfaces has been analyzed by image processing techniques based on the evaluation of images generated by laser light applied on the surface, in order to determine the polishing surface [77]. Another aspect studied in the processes of microinjection of plastics has been the gate location in an injection mold. Applying finite element analysis focused on simulation and using artificial intelligence techniques such as neural networks and genetic algorithms, optimal location values have been obtained, thus minimizing the welding indexes in the mold joining lines, reducing failures in the final product and optimizing the manufacturing process [78].

The use of neural networks and genetic algorithms has been used in the same way in the optimization of the Replication of Injection Molding Light Guide Plates, based on a neural network model that, together with a system of genetic algorithms, seeks an optimal model. The systems propose an evolutionary network that focuses on temperature control by frequency induction is proposed to improve the replication of the micro-characteristics of the molds [79].

The use of artificial intelligence techniques to control the parameters of microinjection has been studied in-depth due to the facilities that show in the management of industrial processes. The use of diffuse systems has been explored to verify and control various variables that are involved in the processes. One study has focused on monitoring and validating the injection rate control to maintain a uniform melt-front velocity during the fill phase compared to the sliding mode and set point control. As a result, a correct follow-up was performed with a minimum error rate [80].

Processes based on fuzzy logic have been studied to serve as support systems in the manufacturing processes of micro plastic parts, making adjustments to the control parameters, giving operators more adjusted values to the design requirements [81].

The field of neural networks has been extensively explored in injection molding processes. Various studies have been carried out in order to characterize behavioral models of injection systems, identifying the most relevant parameters of the processes through the collection, division and processing of available data. The selection of appropriate model inputs, the network architectures together with the network parameters are selected to identify the training algorithms, the learning schemes and the training modes in order to validate the explored models to identify the actual behavior and the optimal values [82].

Learning systems based in neural network and machine learning have been developed in order to give optimal values for machine parameters, without the need to undergo a process of experimentation or simulation, generating a reduction in manufacturing and production times [83]. In the same way, systems based on neural networks have been used in analysis of design and construction of molds, studying the dynamic behavior of the surface temperature of the cavities of the molds, thus generating valuable data that allows improving design efficiency and optimization of processes [84].

Genetic algorithm systems have been developed in order to delve into the analysis of highly variable and non-linear behavior of the polymer injection molding process. Various multivariable systems based on genetic algorithms allow obtaining models of system behavior, achieving optimal values to reduce defect rates and improving dimensional precision and mechanical resistance [85]. The combination of intelligent systems with statistical methods and techniques is widely used in efficiency and optimization processes. The use of mode-pursuing sampling (MPS) with genetic algorithms allows to study the injection processes without the need to resort to a high computational consumption, such as CAE systems, improving the analysis processes and reducing the consumption of resources, both computational and physical [86].

Other studies use back propagation methods together with processes that involve genetic algorithms to carry out studies of the control variables involved in the injection processes, in order to arrive the optimization and the improvement of the processes [87]. Some studies have carried out the combination of system processes involving neural networks and genetic algorithms, along with chemical processes such as the use of microcellular foaming injection, focusing them on practical applications such as the production of vehicle parts with own characteristic of the process [88].

7. METHODOLOGY

The proposed research is an exploratory search framed in the experimental development with a factorial design. The variables of processes and quality parameters of the studied micro plastic parts are correlated, in order to feed the subsystems of each methodological stage to follow.

7.1 HYPOTHESIS

A system that integrates artificial intelligence technologies with CAE simulation in order to determine the geometric and process variables involved in the manufacture of micro plastic parts, improving the efficiency of the process.

7.2 METHODOLOGICAL STAGES

According to the objectives of this project, the methodology to be used will be conceived, integrating the CAE design systems and artificial intelligence technologies for the control of the process variables, in order to determine optimal variables producing any type of generic micro-part with high indexes of quality and productivity.

For the fulfillment of the objectives of the project, the following fields of action and methodological stages are proposed:

1. Design and geometric analysis of the micro-parts: In this field the geometric analysis will be carried out through CAD modeling, which will provide the main geometric variables that affect the quality of the part. This phase includes the analysis of the variations that affect the geometric shape, material complications and imperfections.

2. Analysis of processes by simulation CAE: Simulations of the injection process will be made in order to analyses material behavior when carrying out the process. Different variations will be made on the process variables, to analyses the relationships between injection parameters and to predict the quality characteristic of injection part resulted of combination of parameters.

3. Database creation: Based on the geometric and process analyzes provided by the CAD and CAE simulators, a database will be established where all the results and variations obtained will be recorded. The database must be constituted by all the records that have been generated from the studies carried out, in order to find a behavior that suits the desired indexes.

4. Design of predictive systems based on artificial intelligence: This stage seeks to integrate all the results obtained and stored in the database with an artificial

intelligence expert system, which is able to determine the most appropriate variables to obtain micro-parts with high quality indexes.

5. Validation and implementation: Once the desired results have been obtained and the necessary studies have been carried out, the recommendations generated by the program to validate the correct functioning of the system are put into practice. It is intended that each new test performed serve as information to maximize the database and bring the network to a more real behavior.

This methodology emphasized that the design is an iterative process, therefore, a possible return to previous stages of the process can happen but without falling into an error, rather an improvement of the process.

7.3 MATERIALS

In addition to the use of software design, simulation and programming, it is intended to perform real tests with thermoplastic test materials, such as Polypropylene (PP) and Acrylonitrile Butadiene Styrene (ABS).

7.4 EXCLUSION CRITERIA

The range of measures that will be studied in this project, ranging from a range of milli parts (2 cm maximum) with details of microns in high ranges, (although it will seek to reach as little as possible) that will be delimited by the capabilities that Mold manufacturing is achieved for parts with micro characteristics.

7.5 INSTRUMENTS AND EQUIPMENT

In the different stages previously presented, the following equipment and instruments will be used, which are available in the laboratories of the university:

- Computers: Smart software will be made on the computers of network researchers.
- Microinjection machine and sensory related to the process: The validation tests of the microinjection system will be carried out in the microinjection machine.
- Makerbot 3D printers: the prototyping will be done in the Cube 3D Printer from “Universidad Catolica de Colombia”.

7.6 INNOVATIVE CHARACTER OF THE PROJECT

Although the use of expert systems in control projects has been one of the most explored and analyzed topics in recent years, no real intention has been seen to apply these in real systems, especially in countries like Colombia. Taking this into account, the system proposed will integrate two models of analysis and prediction for the control and generation of variables, which will be able to predict the control of geometric characteristics of material on foot of machine. This is a point innovative to injection industry.

Working with plastic parts with micrometric characteristics that are part of a large system is too complex, in addition to the production and consumption of material to obtain quality parts, so that a system that is capable of giving quality recommendations on the parameters of injection and that guarantees the reduction of cycles of processes, presents a great advantage over the classic processes, especially those that are completely dependent on the operators, where high failure rates and variations on the desired results can be presented. Additionally, this system will be able to learn with each injection cycle, being this capacity another innovative characteristic of this project.

Taking into consideration that today's society is driven by the use of technology, creating programs and systems that help optimize the manufacturing processes of the components that drive technological devices is very useful and important, as these helps to optimize and reduce costs on the manufacture of the components, which helps reduce production times and loss of material.

7.7 POTENTIAL APPLICATION OF RESULTS

- Competitive advantage of the proposal with respect to other existing ones:

    - Since the current manufacturing processes are based on the experience of the operator, the use of an intelligent system that can predict the behavior of a material and give recommendations that optimize the manufacture of plastic parts reducing use of material and production times is a great advantage competitive, that can go hand to hand with the operator without affecting the work position of this and also serving as support.

- Potential markets (national and international):

    - The use of micro plastic parts is fundamental for the proper functioning of technological devices in today's society, so a system that optimizes manufacturing processes and helps reduce production costs is highly appreciated, and if it is exploited correctly can generate large revenues in the thermoplastic manufacturing industry.

7.8 ENVIRONMENTAL IMPACT

The production processes of plastic parts that use injection molding techniques are highly polluting methods, since, starting from the model of injection molding and material, these need high temperatures that are generated from the thermoresistive effect and a high power consumption for feeding the plungers material depression. With the application of a system that improves the efficiency of the process, the reduction of the process cycles is proposed, which significantly reduces the energy and thermal consumption for the feeding of the injection machines.

With the decrease in consumption, the emissions of polluting gases that are generated directly and indirectly in the process are also reduced, reducing pollution levels that affect the environment.

The efficiency in the production bet to him to reduce the consumption of raw material for the injection, that when concentrating in plastic materials (ABS, PP, PI, PO) are in their majority materials of high durability, that are not degradable in the environment and that they generate a more lasting environmental impact.

8. DESCRIPCION OF PROJECT

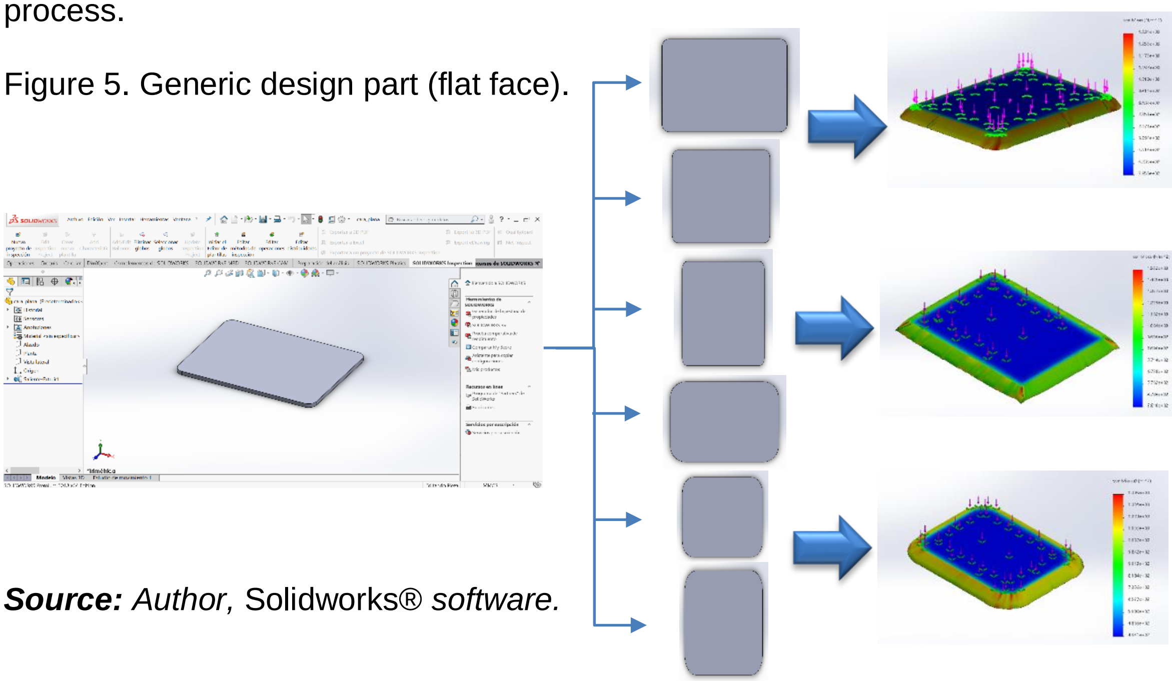
Intelligence system that integrating CAE simulation with expert system technologies allows determining the process parameters and geometric variables involved in the manufacture of plastic parts with micrometric characteristics. The improvement of the efficiency in the process, reducing the injection cycles required to obtain a part of optimal quality conditions. Time reductions, and process material reductions are the result of the apply computational intelligence systems.

Several stages of analysis and experimentation were developed, establishing the most important input variables to be taken into account by the system as well as defining the most relevant injection parameter processes to use them as output variables of the system and their relationships with quality control of parts that require injection processes.

8.1 DESIGN MODELS OF MICRO PLASTIC PARTS

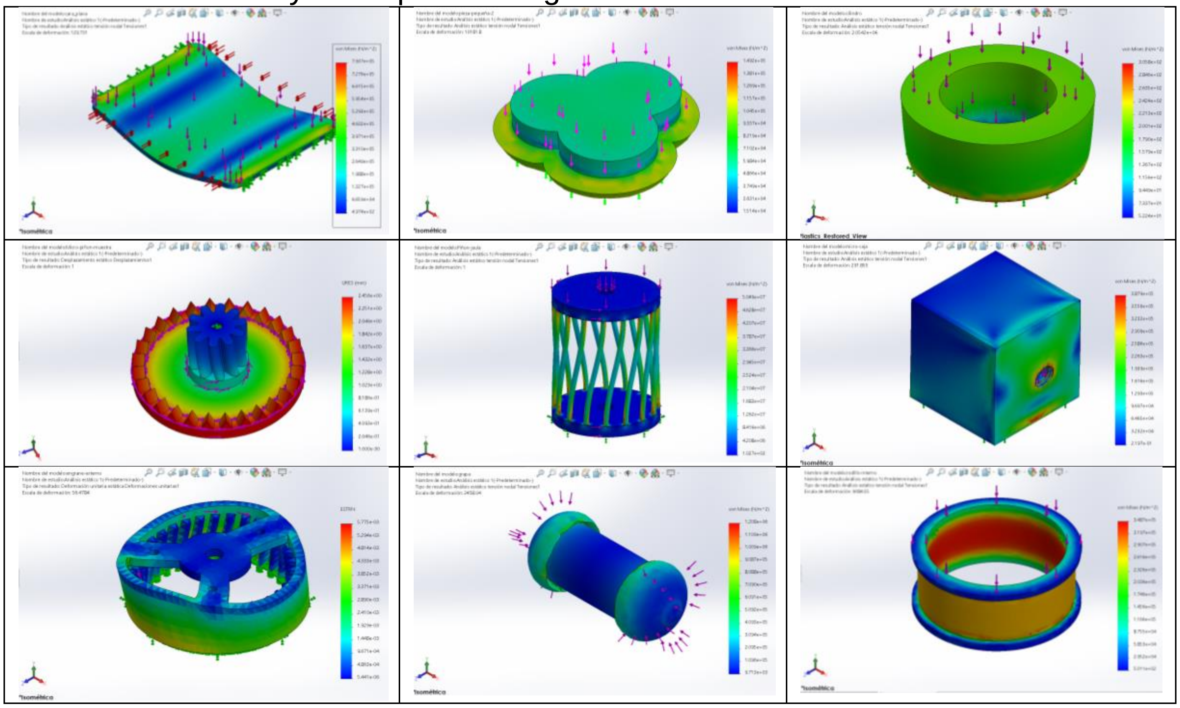
An artificial intelligence system that had a wide range of geometric recognition been necessary to support the micro-manufacturing process. To give at the system the ability to process several geometric variations was decided to design a wide variety of micrometric scale parts that could be used in the production of plastic micro-parts. Through the Solidworks® software, CAD model designs were made with geometric variations that had a generic behavior (basic geometric shapes), in order to design parts for industrial use. 30 different designs of parts were made which were subjected to 6 geometric variations to analyze their behavior before different studies of mechanical stresses. The parts were classified from the generated studies in the parts of the design that best suited for industrial use (see table 2.). All variations of parts would be studied in the injection process and take them to the manufacturing process.

Figure 5. Generic design part (flat face).



Source: *Author,* Solidworks® *software.*

Table 2. Stress analysis on parts with geometric variations.



Source: *Author,* Solidworks® *software.*

8.2 CAE MODEL ANALYSIS OF INJECTION SYSTEM BEHAVIOR

Using the CAE simulation tools provided by the Solidworks® software, different tests were performed to determine how the variation over the injection control variables affected the final result of micro-parts. Based on the initial conditions given by the software, variations were made on parameters such as injection point, material, filling time, material temperature, mold temperature, injection pressure and cooling time. Near 10 types of variations were taken into account by each one of the parameters studied, taking record of each of these and analyzing the final result of the parts against the variation taken (see table 3.).

Table 3. Registered variations injection parameters.

Tmold (°C)	Tmat (°C)	Vol inj (mm^3)	Pinj (Mpa)	Tcool (sec)	Tinj (sec)
36	210	33,5	65	14	16
40	210	35,8	60	6	3
30	219	31.9	86	30	3
36	210	36	61	6	3
37,2	210	35	60	15	6,6
35	210	35,2	58	16.6	17
30	230	31.9	103	29	17
40	210	35	59	6	17
32	**220**	**33**	**76**	**16**	**10**

Source: *Author*

The displacement of material that was generated in the final parts (deformation) was taken as a measure of comparison for the warm analysis of the parts. Each one of the variations that was presented against the variations of the control parameters determining were recorder, identifying in which cases there was a lower deformation and against which variations these cases occurred. All these records were stored in tables for further processing (see table 4.).

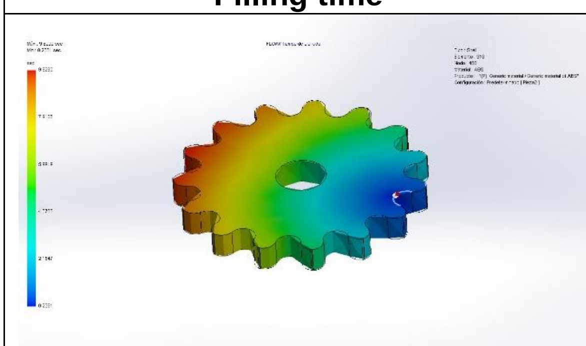
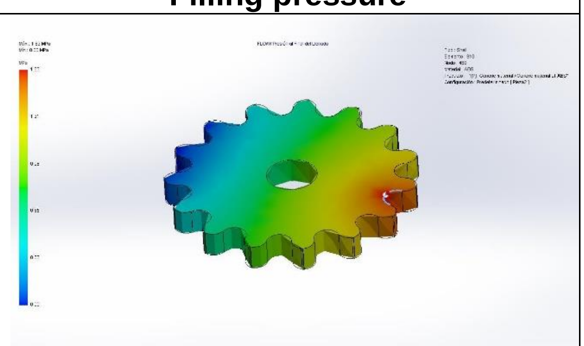
Table 4. Registered displacement over variations of injection parameters.

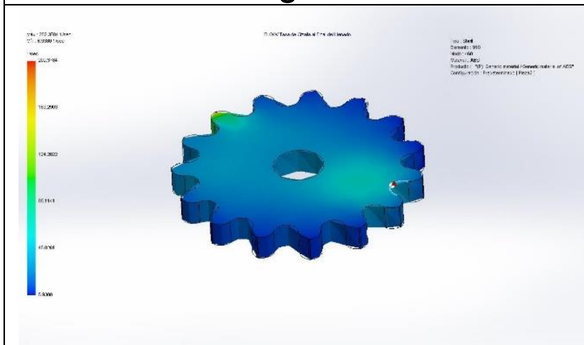
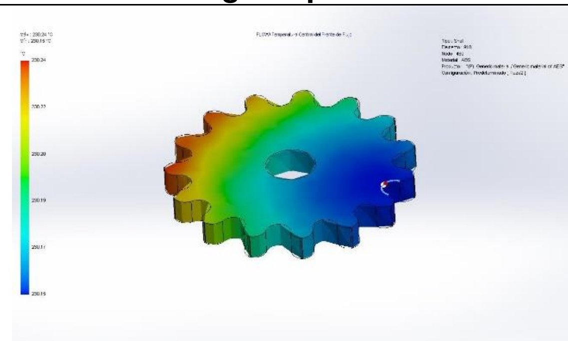
Displacement (X) mm	**Displacement (Y) mm**	**Displacement (Z) mm**	**Displacement (Total) mm**
0,0342	0,0315	0,0379	0,0259
0,1482	0,0272	0,0282	0,075
0,0825	0,2648	0,2612	0,1357
0,0552	0,1953	0,1832	0,1008
0,1491	0,1484	0,1994	0,1265
0,0825	0,2648	0,2612	0,1357
0,3021	0,2966	0,0755	0,1531
0,0821	0,1513	0,1508	0,1009
0,0274	0,0112	0,0118	0,0156

Source: *Author*

Solidworks® Software allows to generate graphical analysis of the behavior of the material in the injection time process simulator; It generated graphs such as temperature, pressure and time during the injection process. All graphics generated by the software were taken into account and stored in a database through behavior analysis (see table 5.). Behavior graphs were generated on the variables obtained and the corresponding graphs were generated from the data provided by the software.

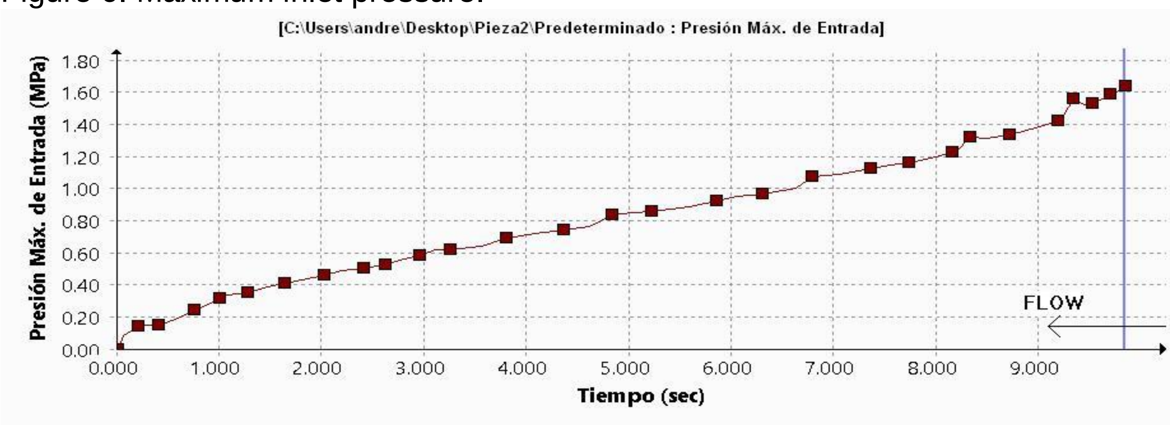
Table 5. Analysis graphics control parameters.

Filling time	**Filling pressure**
	

Filling shear	Filling temperature
	

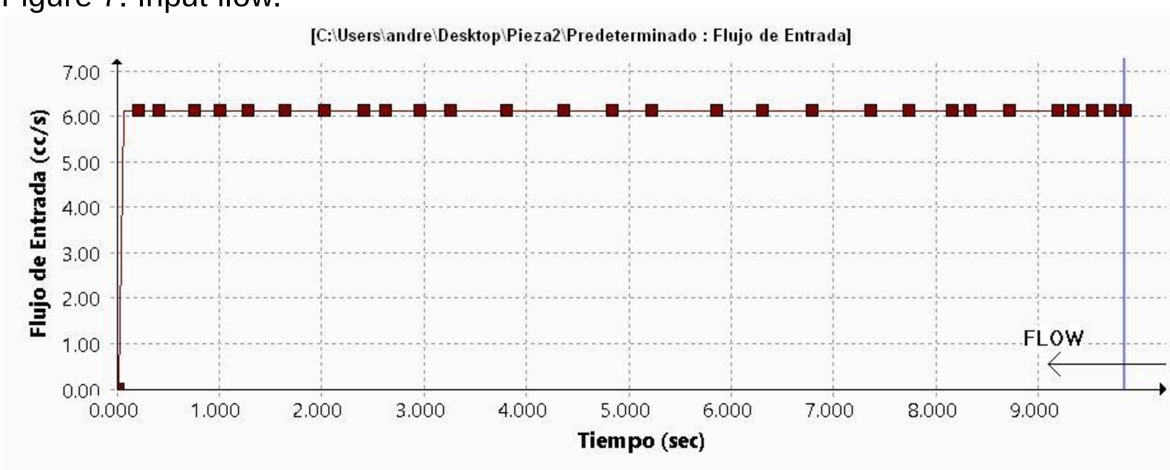
Source: *Author,* Solidworks® *software.*

Figure 6. Maximum inlet pressure.



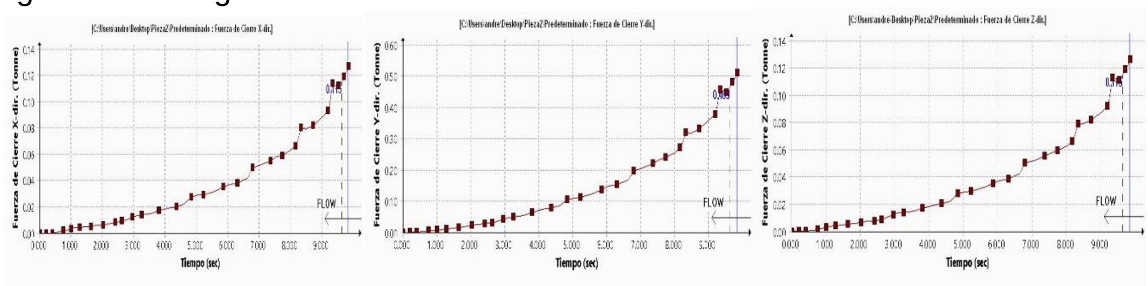
Source: *Author,* Solidworks® *software.*

Figure 7. Input flow.



Source: *Author,* Solidworks® *software.*

Figure 8. Closing force.



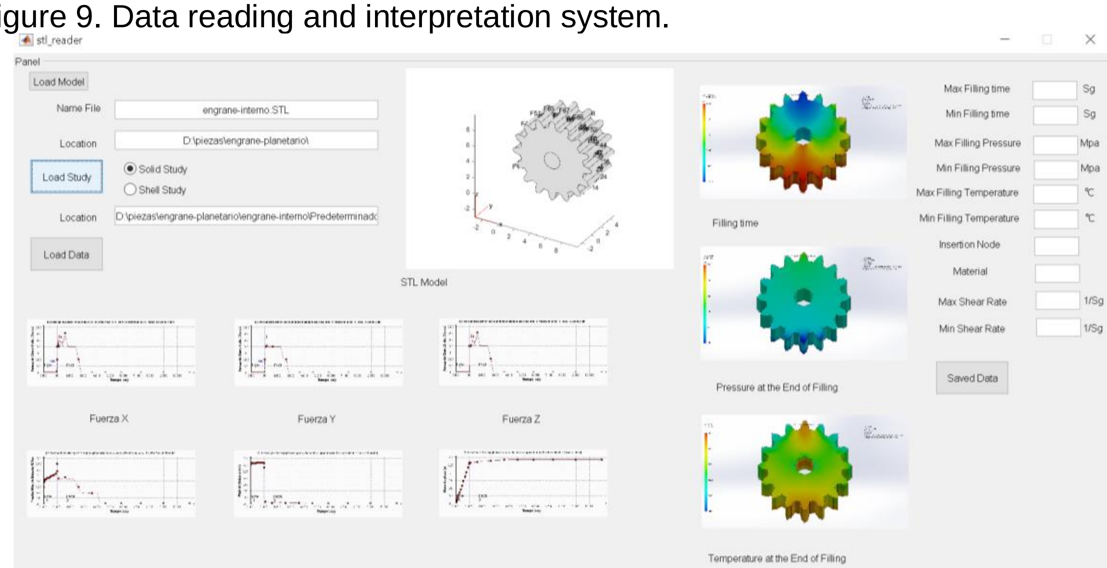
Source: *Author,* Solidworks® *software.*

8.3 DATABASE CREATION BETWEEN CAE MODELS AND INTELLIGENT SYSTEMS.

A large amount of data was generated by all simulations developed, this makes necessary to create a program capable of storing and interpreting all stored data and graphics that occurred during the simulations. Matlab® software was selected to take into account that the vast majority of the data generated is graphic and this software provides a graphical analysis toolbox that facilitates the interpretation and recognition of data provided by all the generated graphics.

A data storage software was designed based on the reading and interpretation of the graphs and the data generated.

Figure 9. Data reading and interpretation system.



Source: *Author,* Matlab® *software.*

The designed system allows the storage of data from the reading and interpretation of the graphs and the generated data. Grayscale images were used by a recognition system based on the binarization of layers. Values between 0 and 1 were managed to search that the positioning of the data was facilitated and could later be taken to real value.

Code of values identification:

Images load:

```
IM1=getimage(handles.axes4);
IM2=getimage(handles.axes5);
IM3=getimage(handles.axes6);
```

Images Processing:

```
IMt1 = imcrop(IM1,[45 118 54 18]);
IMt2 = imcrop(IM1,[42 669 53 18]);
It1 = rgb2gray(IMt1);
It2 = rgb2gray(IMt2);
Bt1 = imresize (It1, [19*20 55*20]);
Bt2 = imresize (It2, [19*20 54*20]);
Bf1 = locallapfilt(Bt1, 0.3, 0.4);
Bf2 = locallapfilt(Bt2, 0.1, 0.1);
Bfn1=imsharpen(Bf1);
Bfn2=imsharpen(Bf2);
Tt1=graythresh(Bfn1);
Tt2=graythresh(Bfn2);
Bfnf1=im2bw(Bfn1,Tt1);
Bfnf2=im2bw(Bfn2,Tt2);
```

OCR application:

```
ocrResults1=ocr(Bfnf1);
ocrResults2=ocr(Bfnf2);
recognizedText1=ocrResults1.Text
recognizedText2=ocrResults2.Text
Xt1 = sum(str2num(recognizedText1));
Xt2 = sum(str2num(recognizedText2));
set(handles.edit4,'string',num2str(Xt1));
set(handles.edit5,'string',num2str(Xt2));
IMp1 = imcrop(IM2,[45 118 54 18]);
IMp2 = imcrop(IM2,[42 669 53 18]);
Ip1 = rgb2gray(IMp1);
Ip2 = rgb2gray(IMp2);
Bp1 = imresize (Ip1, [19*20 55*20]);
Bp2 = imresize (Ip2, [19*20 54*20]);
Bpf1 = locallapfilt(Bp1, 0.3, 0.4);
Bpf2 = locallapfilt(Bp2, 0.3, 0.4);
Bpfn1=imsharpen(Bpf1);
Bpfn2=imsharpen(Bpf2);
```

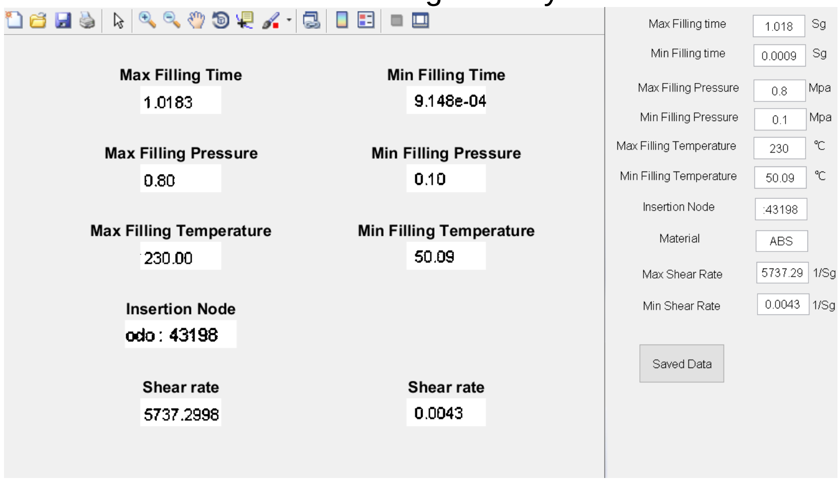
Data recognition:

```
recognizedTextp1=ocrResultsp1.Text;
recognizedTextp2=ocrResultsp2.Text;
```

Data sampling:

```
Xp1 = sum(str2num(recognizedTextp1))
Xp2 = sum(str2num(recognizedTextp2))
set(handles.edit6,'string',num2str(Xp1));
set(handles.edit7,'string',num2str(Xp2));
```

Figure 10. Characterization and data recognition system.



Source: *Author,* Matlab® *software.*

With the recognition system completed, the data was finally stored in tables that can be interpreted and used by subsequent systems.

Table 6. Data storage table.

Material	ABS	ABS	ABS	ABS	PP	PP
Volume (mm^3)	0,24	0,50	0,31	0,05	0,28	0,28
Mass (gr)	0,27	0,55	0,34	0,05	0,25	0,25
X (mm)	14,00	20,00	9,96	4,73	20,00	20,00
Y (mm)	6,10	6,00	5,00	5,00	3,00	3,00
Z (mm)	14,00	20,00	9,96	4,50	5,00	5,00
Filling time (sec)	0,41	0,45	1,01	0,26	0,62	0,62
Material Temperature (°C)	230,00	230,00	230,00	230,00	230,00	230,00
Mold Temperature (°C)	50,00	50,00	50,00	50,00	30,00	30,00
Ejection Temperature (°C)	90,00	90,00	90,00	90,00	95,00	95,00
Injection Pressure (Mpa)	100,00	100,00	100,00	100,00	98,00	1,30
Closing Force X (N)	0,02	0,17	0,03	0,04	0,00	0,00
Closing Force Y (N)	0,03	0,13	0,03	0,01	0,00	0,00
Closing Force Z (N)	0,01	0,16	0,02	0,04	0,00	0,00
Pressure Time (sec)	1,93	1,97	3,02	1,51	17,00	17,00
Cooling Time (sec)	9,41	7,45	24,01	4,76	44,00	44,00
Displacement X (mm)	0,12	0,19	0,10	0,03	0,01	0,01
Displacement Y (mm)	0,12	0,16	0,10	0,03	0,01	0,01
Displacement Z (mm)	0,08	0,07	0,06	0,04	0,01	0,01
Total Displacement (mm)	0,07	0,10	0,05	0,03	0,01	0,01

Source: *Author.*

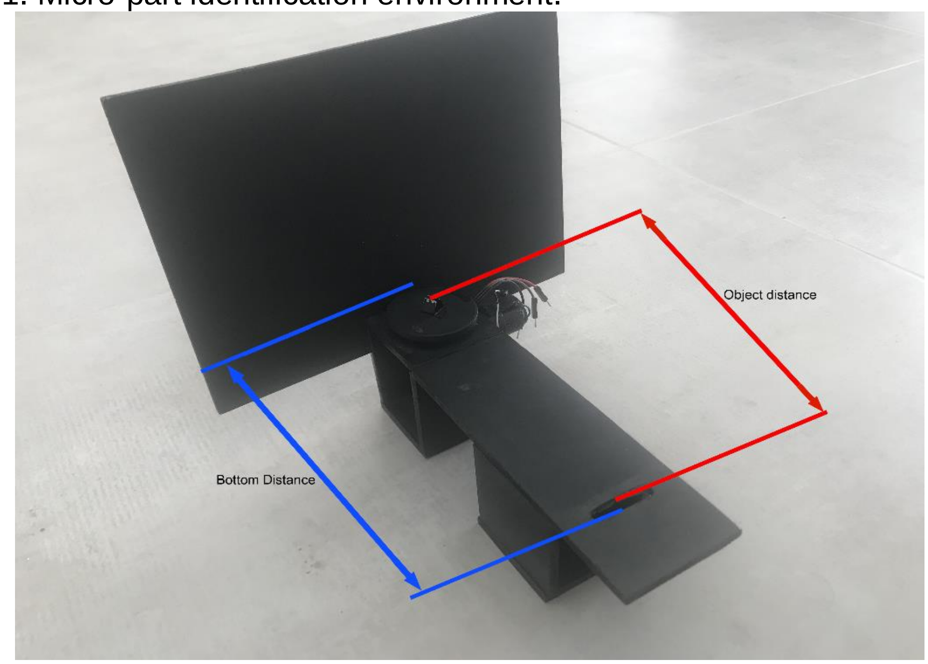
8.4 PREDICTIVE SYSTEM BASED ON NEURAL NETWORKS

Due to a large amount of data collected, an intelligent system based on neural networks was the better option to design. This system must predict the behavior of the control variables of an injection system, determining the better variables to parts with micrometric characteristics that have different geometric shapes. A relationship between the variables and the resulting parts from nonlinear regression determined by the data obtained during the simulations was necessary. A geometric recognition system must be designed for different parts where the dimensions of the geometric figures could be established and the necessary calculations made in the injection process. In the absence of an established mathematical model, a way of relating the intervened variables during the process with the final parts should be sought.

8.4.1 Geometric recognition system.

Three different forms of capture were designed for the geometric recognition system. For the first form, a system capable of recognizing the geometric dimensions of the parts were designed by analyzing pixels from an established distance, for this, a capture environment was designed using an "HP Webcam 1300" camera using an array of pixels identified using image processing, the calculated distance between the depth of the stage, the position of the part and the distance of the camera determining the size of the object studied. A stepper motor is used to rotate the part and analyze each of the corresponding faces determining the height, width, and depth of this.

Figure 11. Micro-part identification environment.



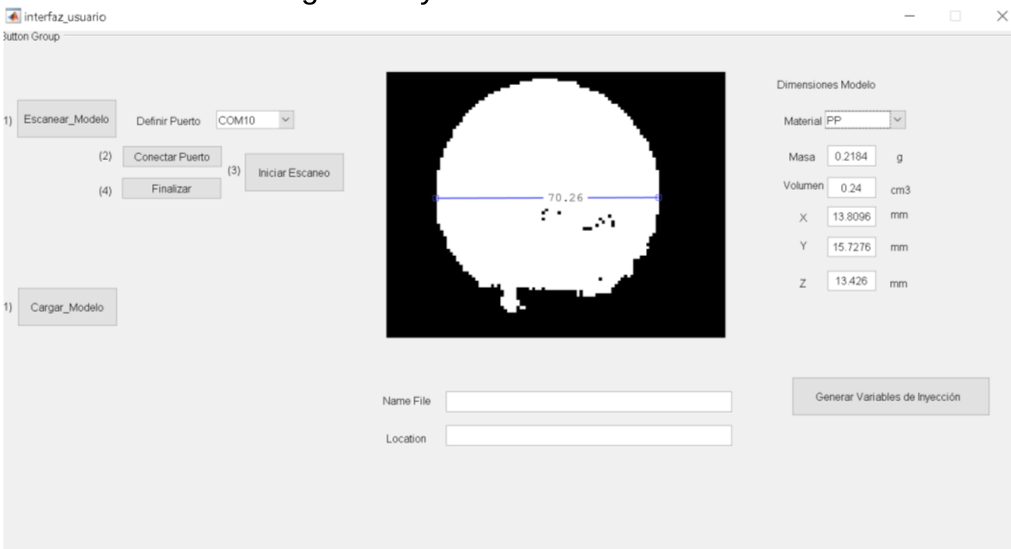
Source: *Author.*

Code of size dimension identification:

Camera recognition:
```
cam = webcam('HP Webcam 1300');
cam.Resolution = '640x480';
comando=4;
```
Image processing
```
Imatrix = [];
for k = 1:12
   preview(cam)
   pause(1)
   Im=snapshot(cam);
   Ins = imcrop(Im,[260.97619047619 326.690476190476 105.714285714286
83.8095238095238]);
   Int = rgb2gray(Ins);
   BInsf1 = locallapfilt(Int, 0.3, 0.4);
   BInsnf1=imsharpen(BInsf1);
   TTin1=graythresh(BInsnf1);
   Binsnf1=im2bw(BInsnf1,TTin1);
   BW2 = bwareaopen(Binsnf1,50);
   images{k} = BW2;
   Imatrix = cat(3, Imatrix, images{k});
   fwrite(s,comando,'uint8');
   pause(1)
   closePreview(cam)
end
figure
imshow3D(Imatrix)
```
Analysis of dimensions
```
for n=1:12
BW2 = images{n};
[f,c]=size(BW2);
for i = 1:f
if sum(BW2(i,:))<=0
BW2(i,:)=1;
elseif sum(BW2(i,:))>=1
BW2(i,:)=BW2(i,:);
end
end
for i = 1:f
   for j = 1:c
      if BW2(i,j)==0
      fiv=i;
      civ=j;
      break
   end
   end
end
Ins2 = imcrop(Ins,[c1iv f1fv c1fv-c1iv f1iv]);
[Alt(n),Anc(n)]=size(Ins2);
end
```
Data conversion:
```
Y=max(Alt)*0.1918;
```

```
X=max(Anc)*0.1918;
Z=min(Anc)*0.1918;
set(handles.edit1,'string',num2str(X));
set(handles.edit2,'string',num2str(Y));
set(handles.edit3,'string',num2str(Z));
axes(handles.axes1);
imshow(images{1})
d = imdistline;
```

Figure 12. Dimension recognition system.



Source: *Author,* Matlab® *software.*

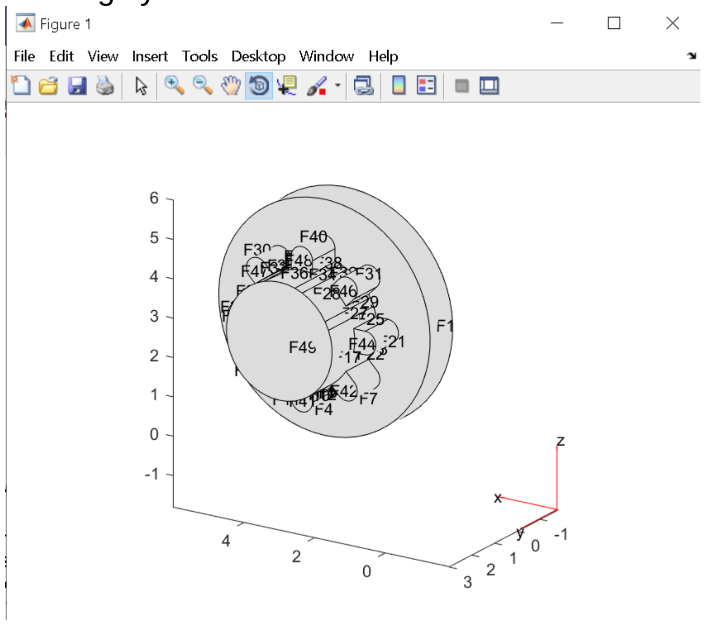
For the second geometric recognition mode, an STL file reading system was designed, this mode is able to recognize the dimensions of all faces of the loaded object and determining the dimensions of each of these by the recognition of the matrix values that each one of these possesses.

Code of STL object face dimension recognition:

```
set(handles.popupmenu2,'visible','on')
set(handles.edit6,'visible','off')
Path=get(handles.edit4,'String');
FileName=get(handles.edit5,'String');
[F,V,N] = stlread([Path FileName]);
vm=max(V);
set(handles.edit1,'string',num2str(vm(1)));
set(handles.edit2,'string',num2str(vm(2)));
set(handles.edit3,'string',num2str(vm(3)));
set(handles.pushbutton5,'visible','on')
```

The system loads the dimensions in the X, Y and Z planes of the studied object in the reading system. Through the definition of the material, the system is able to recognize the volume and weight from the analysis of the dimensions and density of the previously defined material.

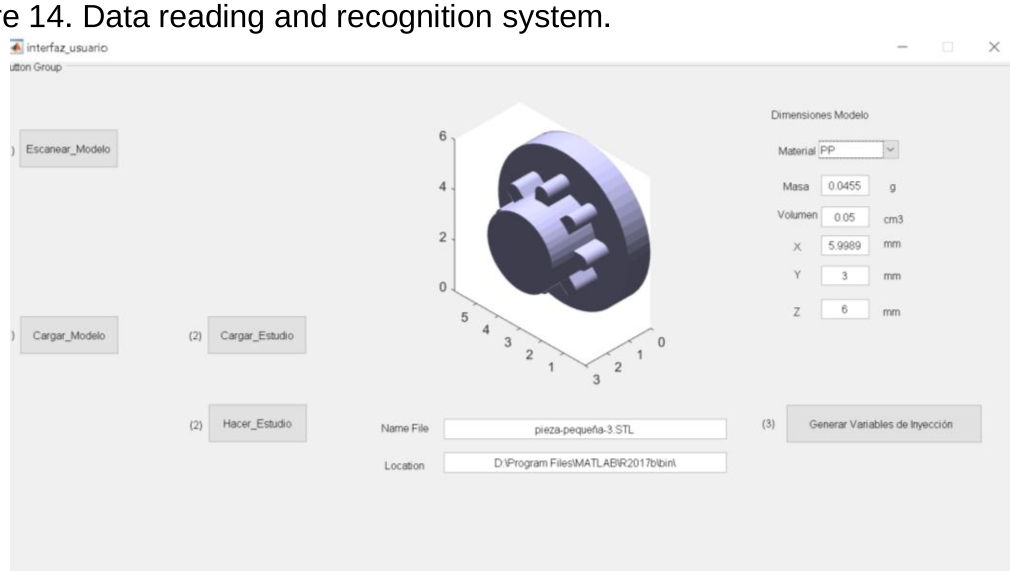
Figure 13. STL file sizing system.



Source: *Author,* Matlab® *software.*

For the third recognition system, code for reading files and character recognition was developed, this allows load the data generated by the Solidworks® software to recognize the dimensions, material, volume and area variables in the neural network system proceeds to work.

Figure 14. Data reading and recognition system.



Source: *Author,* Matlab® *software.*

Solidworks® data reading and recognition code:

Loading data file:

```
[Predeterminado Pathtxt]=uigetfile({'*.html'},'Predeterminado_word');
filetext = fileread([Pathtxt Predeterminado]);
```

Search characters:

```
idnm = strfind(filetext,'Nombre de material =  ');
idnmp=idnm(1)+22;
filetext(idnmp);
c=1;
n=1;
Nombre_de_material(1)=filetext(idnmp);
while c<=2
n=n+1;
if(filetext(idnmp+n)=='<')
c=3;
else
Nombre_de_material(n)=filetext(idnmp+(n-1));
end
end
```

Data recognition:

```
Nombre_de_material(n)=filetext(idnmp+(n-1));
deleteMe = isspace(Nombre_de_material);
Nombre_de_material(deleteMe) = [];
set(handles.edit6,'string',num2str(Nombre_de_material));
c=1;
n=1;
X(1)=filetext(idxp);
while c<=2
n=n+1;
if(filetext(idxp+n)=='(')
c=3;
else
X(n)=filetext(idxp+(n-1));
end
end
deleteMe = isspace(X);
X(deleteMe) = [];
set(handles.edit1,'string',num2str(X));
idy = strfind(filetext,'Y:');
idyp=idy+4;
c=1;
n=1;
Y(1)=filetext(idyp);
while c<=2
n=n+1;
if(filetext(idyp+n)=='(')
c=3;
else
Y(n)=filetext(idyp+(n-1));
end
end
```

```
deleteMe = isspace(Y);
Y(deleteMe) = [];
set(handles.edit2,'string',num2str(Y));
idz = strfind(filetext,'Z:');
idzp=idz+4;
c=1;
n=1;
Z(1)=filetext(idzp);
while c<=2
if(filetext(idzp+n)=='(')
c=3;
else
Z(n)=filetext(idzp+(n-1));
end
end
deleteMe = isspace(Z);
Z(deleteMe) = [];
set(handles.edit3,'string',num2str(Z));
set(handles.pushbutton5,'visible','on')
```

Each of the geometric recognition systems created works in such a way that it is capable of studying the desired objects and analyzing the variables corresponding to the input of the neural network system without generating additional steps or inconveniences when loading the network.

8.4.2 Neural Network Design.

Once a stable system capable of recognizing the different parts with their dimensions was obtained, the design of the neural network began. To analyze the behavioral functions that the neural networks handle was necessary to study the behavior of each one and analyze was better for the desired system in function to develop oriented learning.

Lineal Function:

$$f(x) = \begin{Bmatrix} -1 & x < -\frac{1}{a} \\ a * x & -\frac{1}{a} < x < \frac{1}{a} \\ 1 & \frac{1}{a} < x \end{Bmatrix}$$

Sigmoid function:

$$f(x) = \frac{1}{1 + e^{-gx}}$$

.

Hyperbolic Tangent Function:

$$f(x) = \frac{e^{gx} - e^{-gx}}{e^{gx} + e^{-gx}}$$

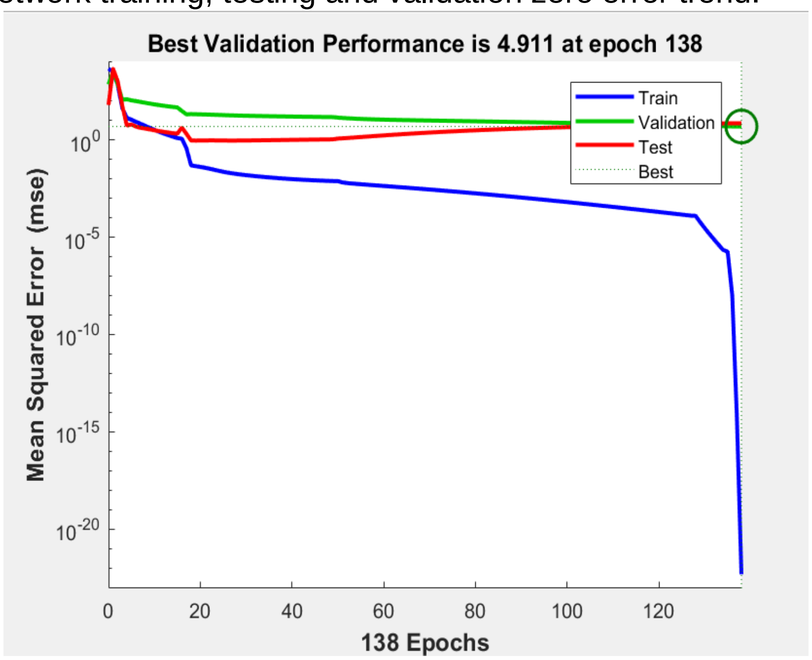
.

To start the neuronal network training, a multilayer network behavior capable of processing the large number of variables handled was sought. As input to the system, the parameters obtained during the simulations in Solidworks® were established. As output were sought control parameters that adjusted to the dimensions of the parts studied and with a zero deformation tendency.

The fact that a mathematical model of the desired system is not established, a model that facilitates analyzing the behavior between the control variables of the injection process and the presence of deformations in injected parts was necessary. A network focused on non-linear regression learning was defined, this is capable to search the behavior between the input and output variables to give an approximation to a behavior function that is established for each part.

To analyze the behavior of the network, different tests were carried out. this allowed the network to focus on a deformation trend that reached zero. As a result, a network behavior with a tendency to zero was obtained, where the behavior of the tests with respect to their validation can be observed.

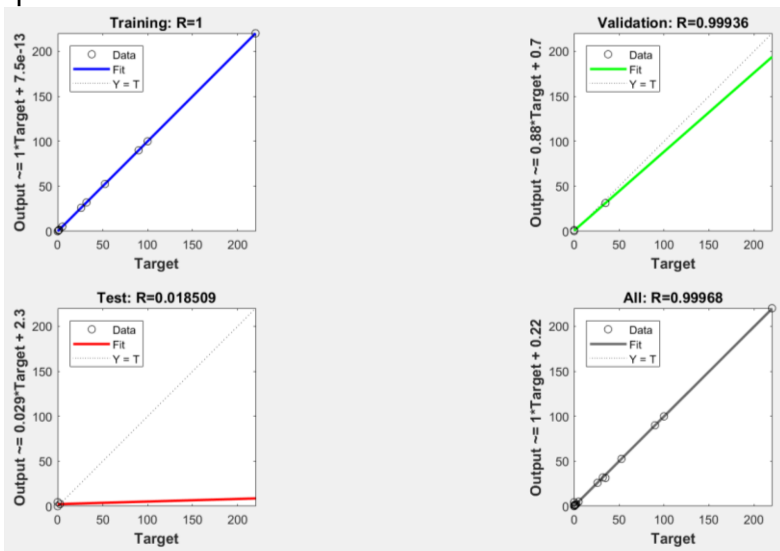
Figure 15. Network training, testing and validation zero error trend.



Source: *Author,* Matlab® *software.*

The behavior of the regression function was validated so the objective values were adapted at the conduct of the functions established by the network. A trend of values that were adapted to the established parameters was observed in order to give the desired results.

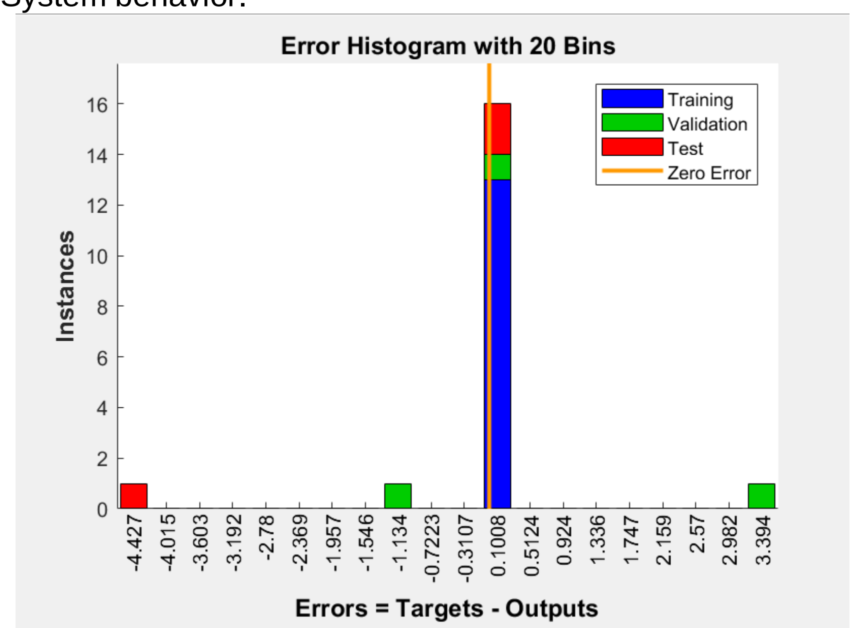
Figure 16. Output validation to behavior function.



Source: *Author,* Matlab® *software.*

The behavior trend of the system was sought, approximately 138 interactions were needed for each part in order to train the network and obtain an approximate behavior of zero, finally, the desired results were obtained with an approximate error of 0.1008.

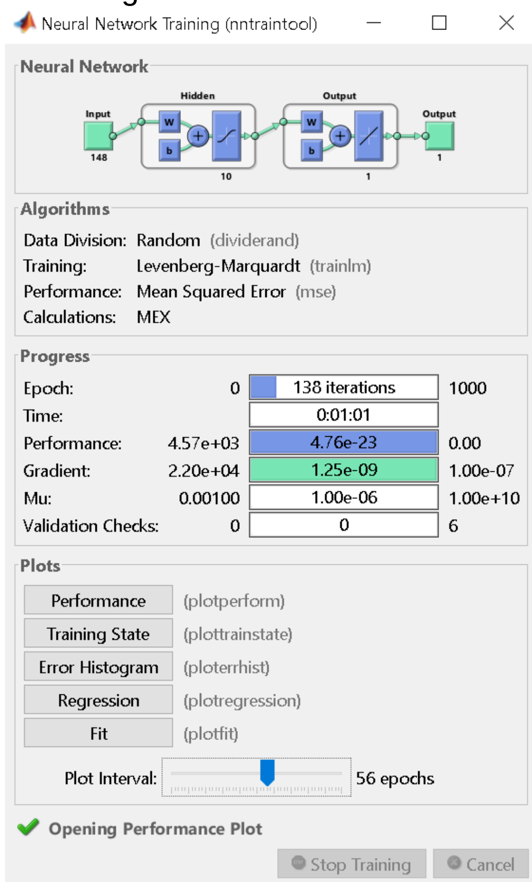
Figure 17. System behavior.



Source: *Author,* Matlab® *software.*

Finally, a neural network composed of 10 internal and one output layer was designed, handling 148 rows of data, made up of 20 control parameter values each one. As output, a single row of data corresponding to the values necessary for the injection process was given.

Figure 18. Neural network designed.



Source: *Author,* Matlab® *software.*

Neuronal network design code:

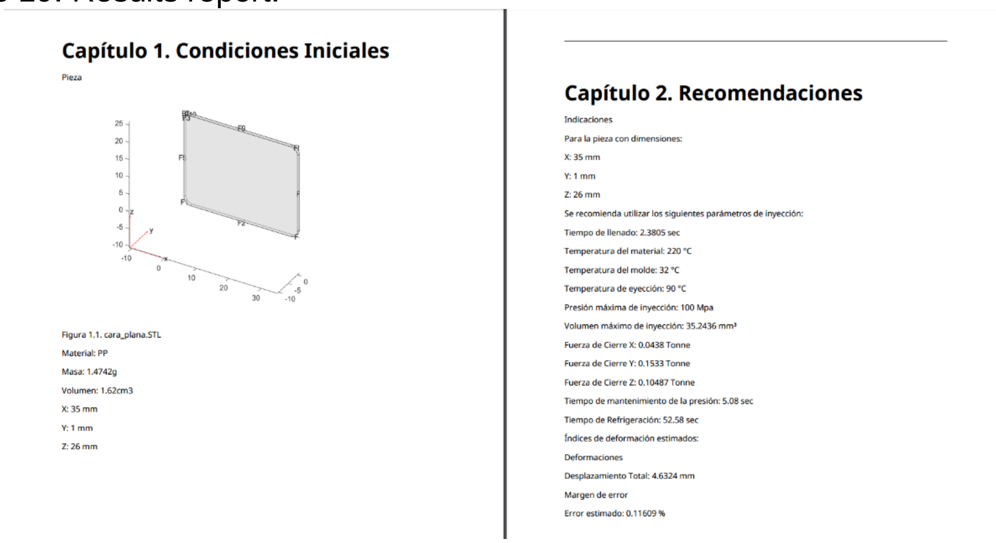
Declaration variables and layers interaction neural network:

```
hiddenLayerSize = 10;
net = fitnet(hiddenLayerSize);
net.divideParam.trainRatio = 70/100;
net.divideParam.valRatio = 15/100;
net.divideParam.testRatio = 15/100;
[net,tr] = train(net,inputs,targets);
outputs = net(inputs);
errors = gsubtract(outputs,targets);
performance = perform(net,targets,outputs);
tInd = tr.testInd;
tstOutputs = net(inputs(:, tInd));
tstPerform = perform(net, targets(tInd), tstOutputs);
view(net)
```

8.4.3 Neural network results.

To publicize the results generated by the network, a PDF file is created by the analysis of the part studied together with the injection parameters recommended. The report is created using a tool provided by Matlab® software, that allows organizing all the data obtained together with the studies carried out so that it is easy for operators to understand.

Figure 19. Results report.



Capítulo 1. Condiciones Iniciales

Pieza

Figura 1.1. cara_plana.STL

Material: PP

Masa: 1.4742g

Volumen: 1.62cm3

X: 35 mm

Y: 1 mm

Z: 26 mm

Capítulo 2. Recomendaciones

Indicaciones

Para la pieza con dimensiones:

X: 35 mm

Y: 1 mm

Z: 26 mm

Se recomienda utilizar los siguientes parámetros de inyección:

Tiempo de llenado: 2.3805 sec

Temperatura del material: 220 °C

Temperatura del molde: 32 °C

Temperatura de eyección: 90 °C

Presión máxima de inyección: 100 Mpa

Volumen máximo de inyección: 35.2436 mm³

Fuerza de Cierre X: 0.0438 Tonne

Fuerza de Cierre Y: 0.1533 Tonne

Fuerza de Cierre Z: 0.10487 Tonne

Tiempo de mantenimiento de la presión: 5.08 sec

Tiempo de Refrigeración: 52.58 sec

Índices de deformación estimados:

Deformaciones

Desplazamiento Total: 4.6324 mm

Margen de error

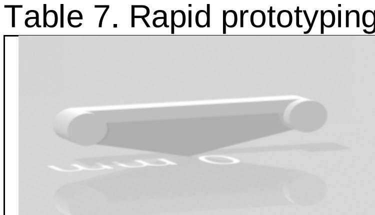
Error estimado: 0.11609 %

Source: *Author,* Matlab® *software, PDF Reader.*

8.5 RAPID PROTOTYPING TESTS FOR DEFECT DETECTION

For the identification of defects in the injection processes, rapid prototyping tests was decided to carry out to identify the defects that may occur. 6 different parts were taken in STL (Standard Triangle Language) format, these were taken to 3d print format for analysis (see table 7.).

Table 7. Rapid prototyping printing parts.

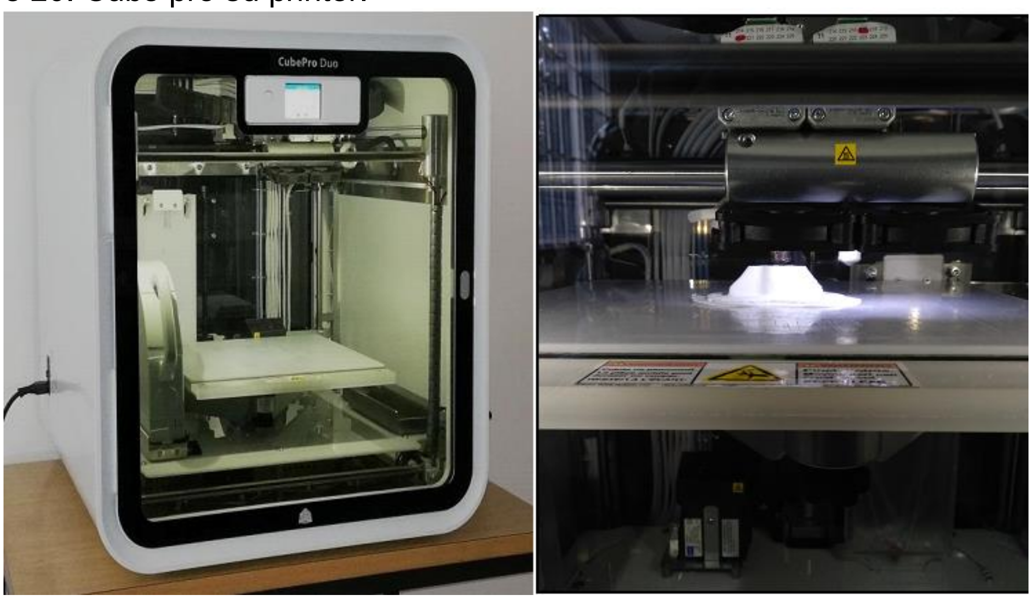
Source: *Author, Print 3D.*

For the analysis of the parts, surface defects were studied and simulated in the rapid prototyping process. As defects were taken those that appear as geometric deformations on a given part, these defects were classified as:

• Sink marks.	Material collapse
• Flash.	Displacement of joint material
• Vacuum venting.	Air accumulations in layers of material
• Burns.	Temperature Marks on the material
• Incomplete parts.	Lack of material to complete the parts

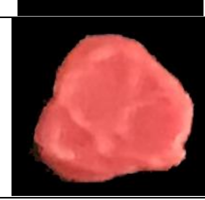
To carry out the corresponding tests, the cube pro 3d printer was used. To analyze the defects that can appear, three base parts were taken to which they applied variations seeking to affect their final geometric shapes. The results parts were classified according to the presented defect (see table 8.).

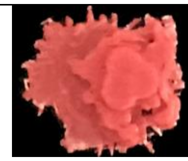
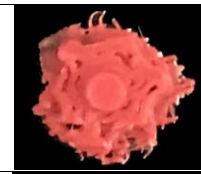
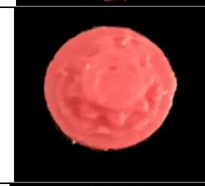
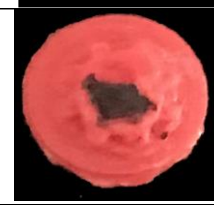
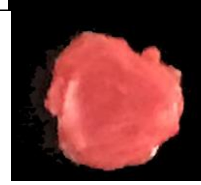
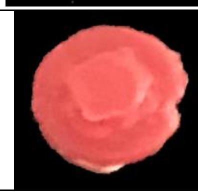
Figure 20. Cube pro 3d printer.



Source: *Author, Universidad Católica De Colombia Laboratory.*

Table 8. Defects in printing parts.

Base part			
Sink marks			

Flash			
Vacuum venting			
Burns			
Incomplete parts			

Source: *Author.*

With the classification of defects, an artificial vision system capable of recognizing the failures studied is proposed, in such a way as to give the indexes of deformation and nonconformity. The indexes are used to proceed with the classification of parts and the management of the database.

8.5.1 Artificial vision for recognition of defects.

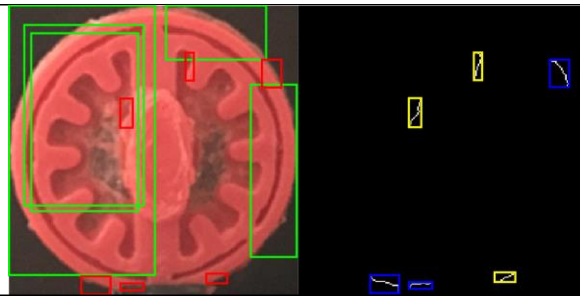
Starting from the vision system used for the recognition of dimensions, recognition algorithms were created for the detection of defects. Parts of a millimeter and micrometric dimensions are handling, with micrometric characteristics, thinking in this, a high-resolution camera capable of detecting the defects that appear on the part were necessary to implement. A Logitech HD Pro webcam 1080p was used for the resolution it manages, capable of capturing and detecting all the characteristics of the parts used.

A geometric recognition system was designed taking from a database of binary images. It makes a comparison between the captured images and the base images. Using the results of the comparison, the geometrical differences between one image and another are analyzed by region props, pixels with defects are analyzed and classified according to size and shape. Analyze the RGB layers of the images that were implemented to detect chromatic differences that can be considered as burns on the parts. Finally, the affected areas were analyzed and a percentage was obtained to indicate the index of involvement of the resulting part.

Table 9. Recognition and characterization of defects by artificial vision.

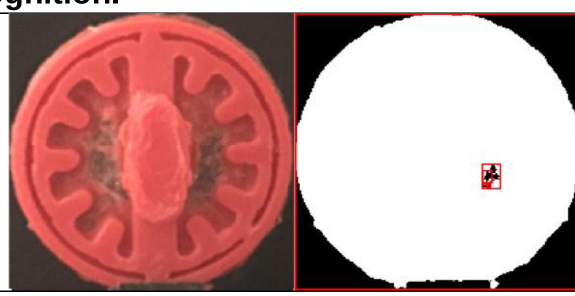
Flash and Vacuum venting recognition:

- The system performs detection of objects identifying those where there are variations in shape. Identify the most critical parts of the part and from area analysis determine which can be classified as Vacuum venting and Flash.
- **Interest areas.**
- **Flaw detection.**
- **Vacuum venting.**
- **Flash.**



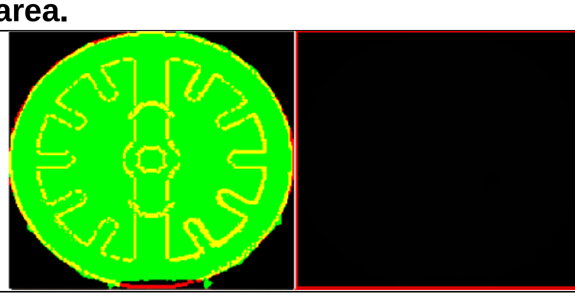
Burn recognition:

- Through the analysis of RGB capable, layer by layer is studied, identifying the chromatic variations that appear on the material, the affected area is identified and the indices of affectation are obtained.
- **Area recognition.**



incomplete part recognition:

- By segmentation of areas and edge search, the geometric shape of the studied part is identified, a comparison is made with the base of existing figures and incomplete areas are determined.
- **Area comparison.**
- **Affected area.**



Source: *Author.*

Recognition code for artificial vision:

Camera recognition:
```
cam = webcam('Logitech® HD Pro webcam 1080p');
cam.Resolution = '1280x720';
preview(cam)
Im=snapshot(cam);
```
Image processing:
```
B = imguidedfilter(Im);
Int = rgb2gray(B);
imad = imadjust(Int);
sharpCoeff = [0 0 0;0 1 0;0 0 0]-fspecial('laplacian',0.9);
imgSharp = imfilter(imad,sharpCoeff,'symmetric');
I2 = imfill(imgSharp);
BW2 = edge(I2,'sobel');
difabs1 = bwareaopen(BW2, 15);
closePreview(cam)
difabs1 = imcrop(difabs1,[522 289 220 220]);
imgj= imcrop(Im,[522 289 220 220]);
img= difabs1;
imshow(imgj)
[L Ne]=bwlabel(difabs1);
propied= regionprops(L);
```
Recognition interest areas:
```
hold on
for n=1:size(propied,1)
rectangle('Position',propied(n).BoundingBox,'EdgeColor','g','LineWidth',2)
end
pause (3)
s=find([propied.Area]<40);
for n=1:size(s,2)
rectangle('Position',propied(s(n)).BoundingBox,'EdgeColor','r','LineWidth',2)
end
pause (2)
for n=1:size(s,2)
   d=round(propied(s(n)).BoundingBox);
   difabs1(d(2):d(2)+d(4),d(1):d(1)+d(3))=0;
end
C = imfuse(img,difabs1,'falsecolor','Scaling','joint','ColorChannels',[1 2 0]);
im_g =(C(:,:,2)) ;
[f c]=size(im_g);
for i=1:f
for j=1:c
   mat(i,j)=C(i,j)-im_g(i,j);
end
end
```

8.6 DEFECT ANALYSIS FUZZY LOGIC SYSTEM

Due to the fact that the possible flaws of defects that may appear on the micro-parts depend, not only on the control parameters, also on external factors such as temperature, humidity, material quality, among others. To reduce these external factors is necessary to use an intelligent accompaniment system that classifies and identifies the faults present for each new injection cycle and helps operators reduce possible defects that may occur. A system based on fuzzy logic was proposed for the analysis of qualitative values to be performed on the detected defects.

8.6.1 Mathematical model detection for defects.

From the analyses carried out by simulation and detection of defects was identified that the variations on the control parameters can affect the result of the micro-parts. Each of the possible defects that can appear in the injected micro-parts has a direct relationship on the control parameters, so it was necessary to identify a mathematical model that approximates the actual behavior of the relationships between "defect-variable".

Applied polynomial regression, the behavior that occurred between the presence of defects and the variation between injection parameters was studied. Main defects were analyzed to finding an approximate model of the behavior that occurred between the changes of variations. As a result, the models were obtained.

Vacuum venting function by:

- Injection pressure: $y = 0.0064 * x^2 + 0.0101 * x - 0.0165$
- Material temperature: $y = -0.0035 * x^2 + 0.0845 * x - 0.0810$
- Melt temperature: $y = 0.0021 * x^2 + 0.0399 * x - 0.0420$
- Fill time: $y = -0.0064 * x^2 + 0.1485 * x - 0.1421$
- Injection volume: $y = -0.0073 * x^2 + 0.1492 * x - 0.1419$

Burns function by:

- Injection pressure: $y = -0.0070 * x^2 + 0.1334 * x - 0.1264$
- Material temperature: $y = -0.0025 * x^2 + 0.0735 * x - 0.0710$
- Melt temperature: $y = -0.0071 * x^2 + 0.1394 * x - 0.1323$
- Fill time: $y = -0.0033 * x^2 + 0.1280 * x - 0.1247$
- Injection volume: $y = -0.0043 * x^2 + 0.0954 * x - 0.0911$

Incomplete parts function by:

- Injection pressure: $y = 0.0047 * x^3 - 0.1036 * x^2 + 0.7608 * x - 0.9482$
- Material temperature: $y = -0.0074 * x^2 + 0.1672 * x - 0.1598$
- Melt temperature: $y = -0.0131 * x^2 + 0.2049 * x - 0.1918$
- Fill time: $y = -0.0019 * x^2 + 0.1095 * x$
- Injection volume: $y = 0.0072 * x^2 + 0.0272 * x - 0.0344$

Flash function by:

- Injection pressure: $y = -0.0071 * x^2 + 0.1578 * x - 0.1507$
- Material temperature: $y = 0.0021 * x^2 + 0.0399 * x - 0.0420$
- Melt temperature: $y = -0.0014 * x^2 + 0.1061 * x - 0.1047$
- Fill time: $y = 0.0150 * x^2 - 0.0924 * x - 0.1422$
- Injection volume: $y = -0.0067 * x^2 + 0.1471 * x - 0.1404$

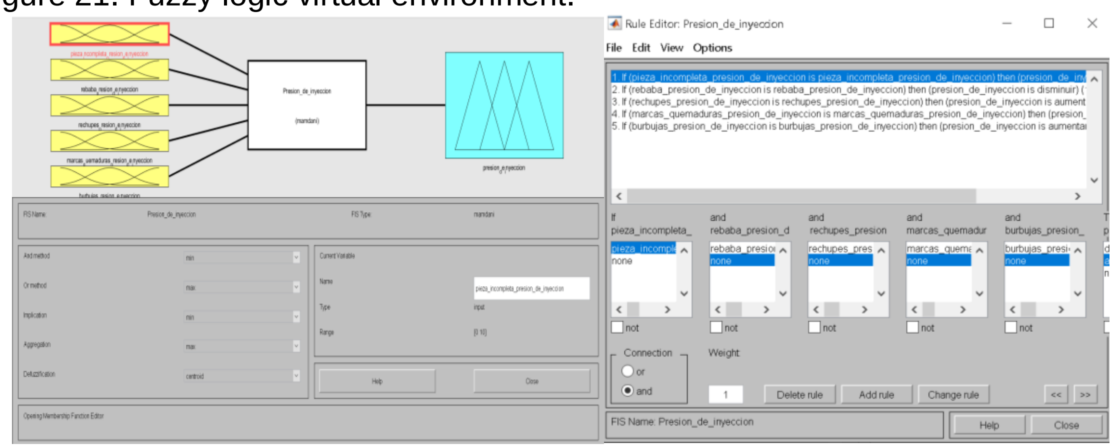
Sink marks function by:

- Injection pressure: $y = -0.0102 * x^2 + 0.1578 * x - 0.1507$
- Material temperature: $y = -0.0069 * x^3 + 0.1386 * x^2 - 0.7664 * x - 1.2896$
- Melt temperature: $y = 0.0027 * x^2 + 0.0610 * x - 0.0637$
- Fill time: $y = 0.0018 * x^2 - 0.0806 * x - 0.0824$
- Injection volume: $y = -0.0073 * x^2 + 0.1492 * x - 0.1429$

8.6.2 fuzzy logic functions call.

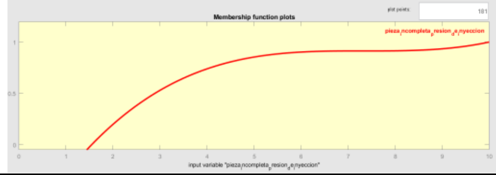
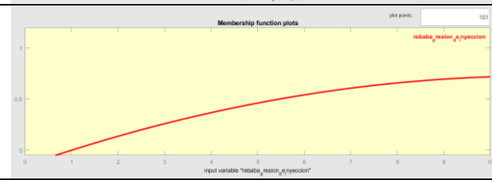
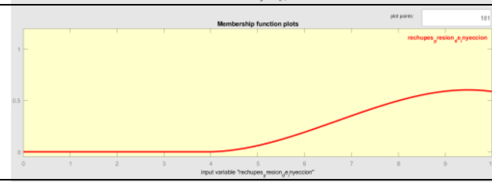
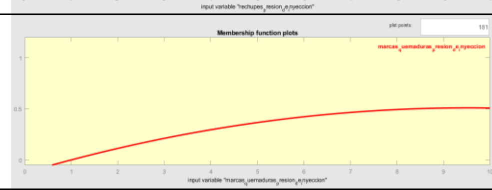
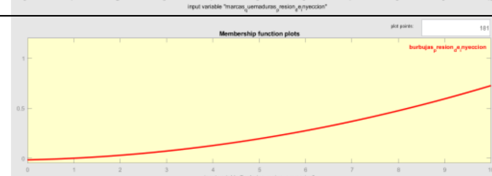
Matlab® software offers a completely virtual environment focused on fuzzy logic. Function blocks were created from the models obtained for the behavior between "variable-defect", by each function block was necessary to create a different interface where the control parameters were analyzed with the defects according to their behavioral function. Fuzzy logic is governed by compliance with conditional type rules. Matlab® software needs to declare the rules with which the system will perform the functional analysis for each variable. Five different environments with their respective behavior were obtained.

Figure 21. Fuzzy logic virtual environment.



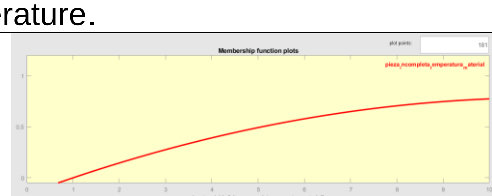
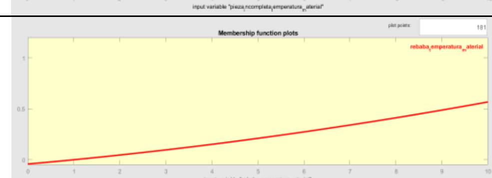
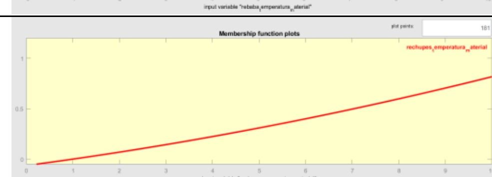
Source: *Author,* Matlab® *software.*

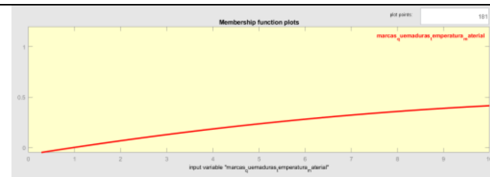
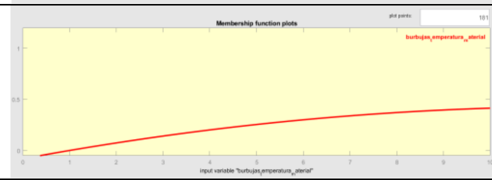
Table 10. Behavior functions injection pressure.

Incomplete Part: $\mathbf{y = 0.0047 * x^3 - 0.1036 * x^2 + 0.7608 * x - 0.9482}$	
Flash: $\mathbf{y = -0.0071 * x^2 + 0.1578 * x - 0.1507}$	
Sink marks: $\mathbf{y = -0.0102 * x^2 + 0.1578 * x - 0.1507}$	
Burn: $\mathbf{y = -0.0070 * x^2 + 0.1334 * x - 0.1264}$	
Vacuum venting: $\mathbf{y = 0.0064 * x^2 + 0.0101 * x - 0.0165}$	

Source: *Author,* Matlab® *software.*

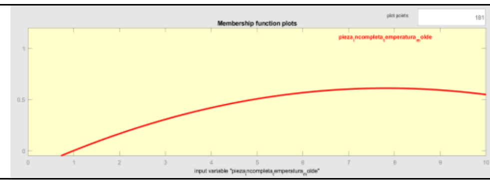
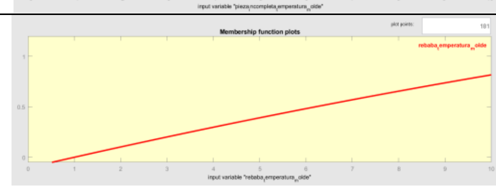
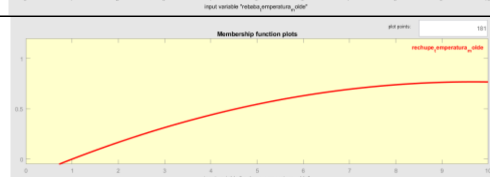
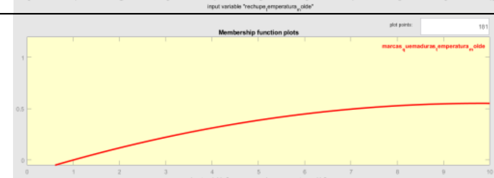
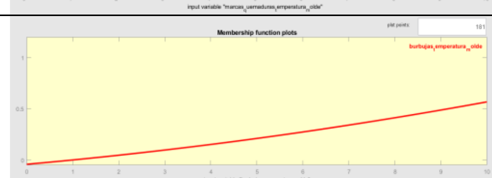
Table 11. Behavior functions material temperature.

Incomplete Part: $\mathbf{y = -0.0074 * x^2 + 0.1672 * x - 0.1598}$	
Flash: $\mathbf{y = 0.0021 * x^2 + 0.0399 * x - 0.0420}$	
Sink marks: $\mathbf{y = -0.0069 * x^3 + 0.1386 * x^2 - 0.7664 * x - 1.2896}$	

Burn: $$y = -0.0025 * x^2 + 0.0735 * x - 0.0710$$	
Vacuum venting: $$y = -0.0035 * x^2 + 0.0845 * x - 0.0810$$	

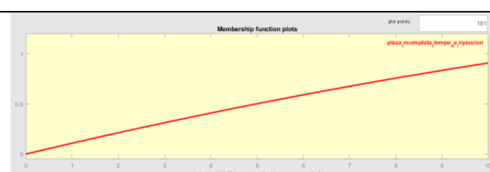
Source: *Author,* Matlab® *software.*

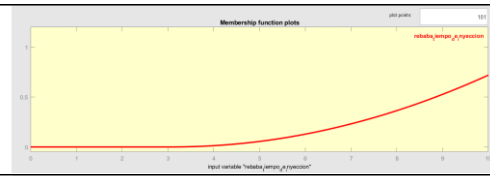
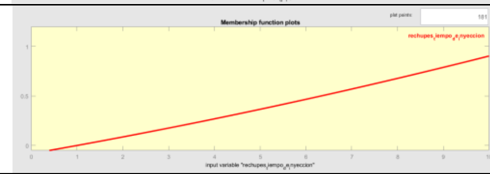
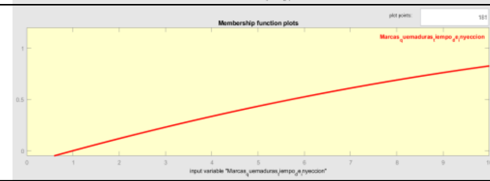
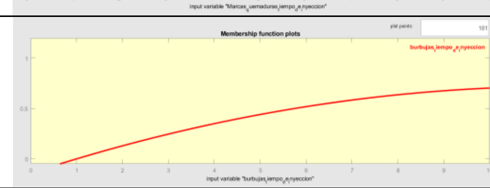
Table 12. Behavior functions melt temperature.

Incomplete Part: $$y = -0.0131 * x^2 + 0.2049 * x - 0.1918$$	
Flash: $$y = -0.0014 * x^2 + 0.1061 * x - 0.1047$$	
Sink marks: $$y = 0.0027 * x^2 + 0.0610 * x - 0.0637$$	
Burn: $$y = -0.0071 * x^2 + 0.1394 * x - 0.1323$$	
Vacuum venting: $$y = 0.0021 * x^2 + 0.0399 * x - 0.0420$$	

Source: *Author,* Matlab® *software.*

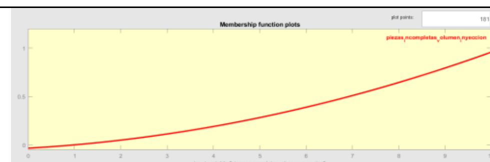
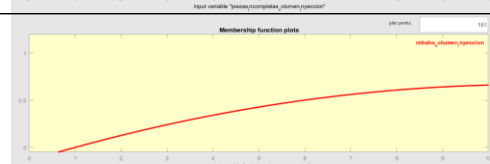
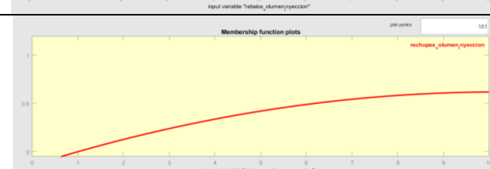
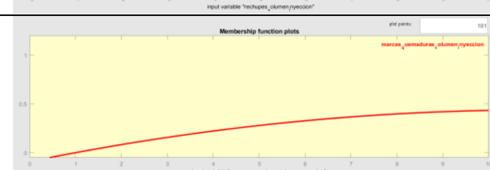
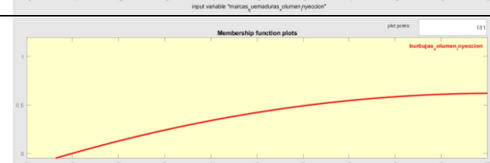
Table 13. Behavior functions fill time.

Incomplete Part: $$y = -0.0019 * x^2 + 0.1095 * x$$	

Flash: $$y = 0.0150 * x^2 - 0.0924 * x - 0.1422$$	
Sink marks: $$y = 0.0018 * x^2 - 0.0806 * x - 0.0824$$	
Burn: $$y = -0.0033 * x^2 + 0.1280 * x - 0.1247$$	
Vacuum venting: $$y = -0.0064 * x^2 + 0.1485 * x - 0.1421$$	

Source: *Author,* Matlab® *software.*

Table 14. Behavior functions Injection volume.

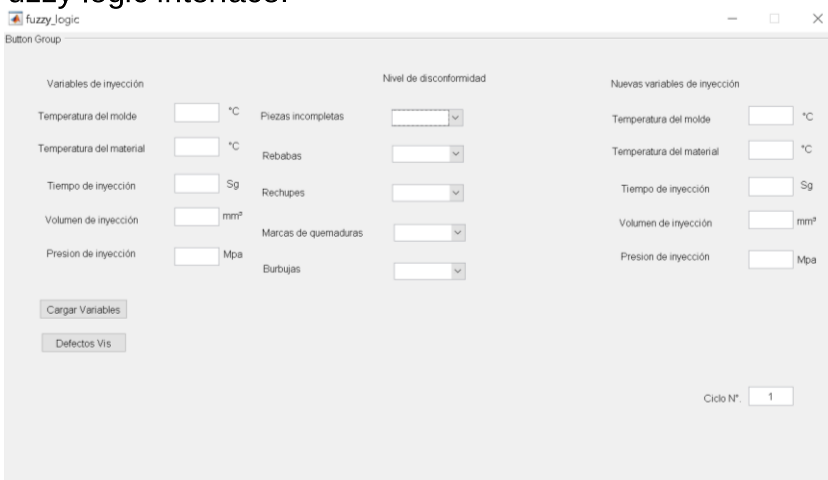
Incomplete Part: $$y = 0.0072 * x^2 + 0.0272 * x - 0.0344$$	
Flash: $$y = -0.0067 * x^2 + 0.1471 * x - 0.1404$$	
Sink marks: $$y = -0.0073 * x^2 + 0.1492 * x - 0.1429$$	
Burn: $$y = -0.0043 * x^2 + 0.0954 * x - 0.0911$$	
Vacuum venting: $$y = -0.0073 * x^2 + 0.1492 * x - 0.1419$$	

Source: *Author,* Matlab® *software.*

8.6.3 Fuzzy logic system interface.

In order to create a user-friendly and easy-to-use system, an interface for the use of a qualitative micro-parts rating was designed. Using the Matlab® software, a loading window was created where the latest control parameters loaded into the system were recognized. A qualitative system was designed that allows the incidence rates of micro-parts to be analyzed without having to resort to numerical values.

Figure 22. Fuzzy logic interface.



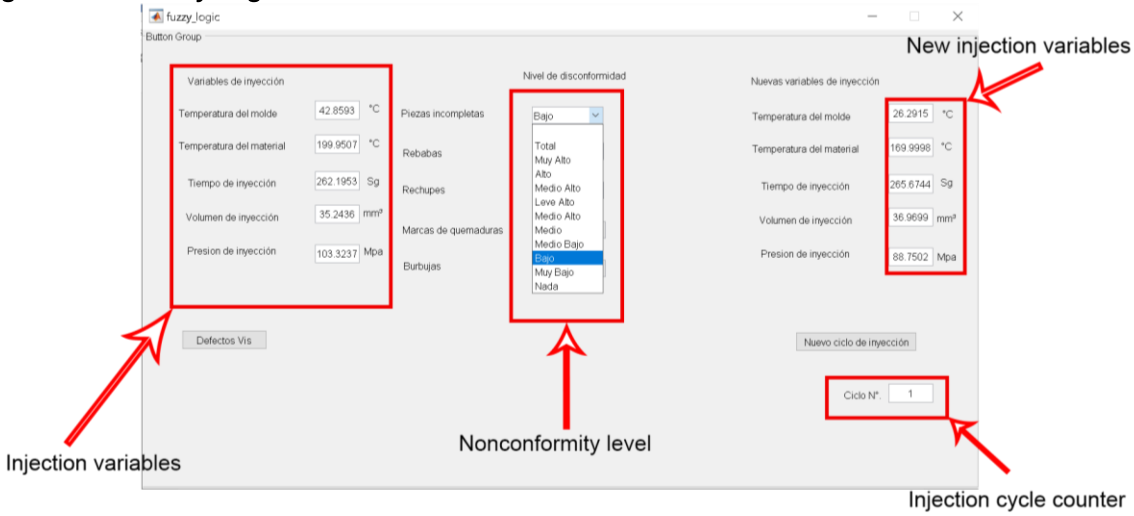
Source: *Author,* Matlab® *software.*

The indices of defects in micro-parts were rated by:

- Total.
- Very high.
- High.
- Medium high.
- Slight high.
- Medium.
- Medium low.
- Low.
- Very low.
- Nothing.

According to the operator's criteria, the deformation index is indicated in the interface, this used the polynomial functions of the behavior of the variables. New values are obtained in order to reduce the failures that may occur in the micro-parts. An artificial vision analysis option was also created based on the defect recognition code.

Figure 23. Fuzzy logic interface control.



Source: *Author,* Matlab® *software.*

Code called fuzzy logic functions:

Called variables

```
global pieza_incompleta
global rebabas
global rechupes
global marcas_quemaduras
global burbujas
Temperatura_molde = readfis('Temperatura_molde');
Temperatura_material = readfis('Temperatura_material');
Tiempo_de_inyeccion= readfis('Tiempo_de_inyeccion');
volumen_de_inyeccion= readfis('volumen_inyeccion');
Presion_de_inyeccion= readfis('Presion_de_inyeccion');
Temperatura_molde =
```

Injection Variables call:

```
setfis(Temperatura_molde,'output',1,'range',[Temp_mold-50 Temp_mold+50]);
Temperatura_molde = setfis(Temperatura_molde,'output',1,'mf',1,'params',[-1000
Temp_mold-50 Temp_mold]);
Temperatura_molde = setfis(Temperatura_molde,'output',1,'mf',2,'params',[Temp_mold
Temp_mold+50 1000]);
Temperatura_material = setfis(Temperatura_material,'output',1,'range',[Temp_mat-115
Temp_mat+115]);
Temperatura_material = setfis(Temperatura_material,'output',1,'mf',1,'params',[-1000
Temp_mat-115 Temp_mat]);
Temperatura_material = setfis(Temperatura_material,'output',1,'mf',2,'params',[Temp_mat
Temp_mat+115 1000]);
Tiempo_de_inyeccion = setfis(Tiempo_de_inyeccion,'output',1,'range',[Tim_iny-15
Tim_iny+15]);
Tiempo_de_inyeccion = setfis(Tiempo_de_inyeccion,'output',1,'mf',1,'params',[-1000
Tim_iny-15 Tim_iny]);
Tiempo_de_inyeccion = setfis(Tiempo_de_inyeccion,'output',1,'mf',2,'params',[Tim_iny
Tim_iny+15 1000]);
```

```
volumen_de_inyeccion = setfis(volumen_de_inyeccion,'output',1,'range',[Vol_iny-22.5
Vol_iny+22.5]);
volumen_de_inyeccion = setfis(volumen_de_inyeccion,'output',1,'mf',1,'params',[-1000
Vol_iny-22.5 Vol_iny]);
volumen_de_inyeccion = setfis(volumen_de_inyeccion,'output',1,'mf',2,'params',[Vol_iny
Vol_iny+22.5 1000]);
Presion_de_inyeccion = setfis(Presion_de_inyeccion,'output',1,'range',[Pres_iny-65
Pres_iny+65]);
Presion_de_inyeccion = setfis(Presion_de_inyeccion,'output',1,'mf',1,'params',[-1000
Pres_iny-65 Pres_iny]);
Presion_de_inyeccion = setfis(Presion_de_inyeccion,'output',1,'mf',2,'params',[Pres_iny
Pres_iny+65 1000]);
```

Outputs of new variables:

```
output_Temperatura_molde = evalfis([pieza_incompleta rebabas rechupes
marcas_quemaduras burbujas],Temperatura_molde);
output_Temperatura_material = evalfis([pieza_incompleta rebabas rechupes
marcas_quemaduras burbujas],Temperatura_material);
output_Tiempo_de_inyeccion = evalfis([pieza_incompleta rebabas rechupes
marcas_quemaduras burbujas],Tiempo_de_inyeccion);
output_volumen_de_inyeccion = evalfis([pieza_incompleta rebabas rechupes
marcas_quemaduras burbujas],volumen_de_inyeccion);
output_Presion_de_inyeccion = evalfis([pieza_incompleta rebabas rechupes
marcas_quemaduras burbujas],Presion_de_inyeccion);
```

Finally, all the data generated by each injection cycle are used to feed the database and adjust it to each injection machinery and process.

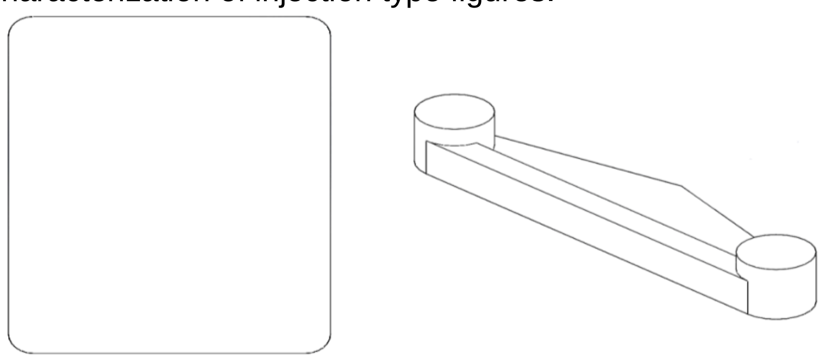
9. RESULTS

Intelligent systems applied to a process that has been carried out for years through learning and the experience acquired is a complicated task, when having to create systems capable of making decisions as an operator with a long history would do, which has allowed him to acquire instincts for handling the machinery and the resulting parts.

The decision to start from the design of parts with micrometric characteristics allows studying the behavior that occurs during the injection processes. With the analysis of how the shape of the parts can affect the final designs were recognized the geometric patterns that most affect the manufacture of plastic micro-parts and that can generate problems, both in the design of molds and in the process of injection of the material.

When handling parts of a millimeter and micrometric dimensions, as a result, the management of basic geometries show that allows better results in the injection processes. The general classification of the geometric patterns was given by:

Figure 24. Characterization of injection type figures.



Source: *Author,* design models of micro plastic parts with different geometric characteristic.

- 2D flow features: Parts of basic geometric designs that have a single face given by the type of mold and the injection mode (left.).
- 3D flow features: Parts of three-dimensional geometric shapes that have two or more faces that are formed by the mold, the injection cavities and the injection mode (right.).

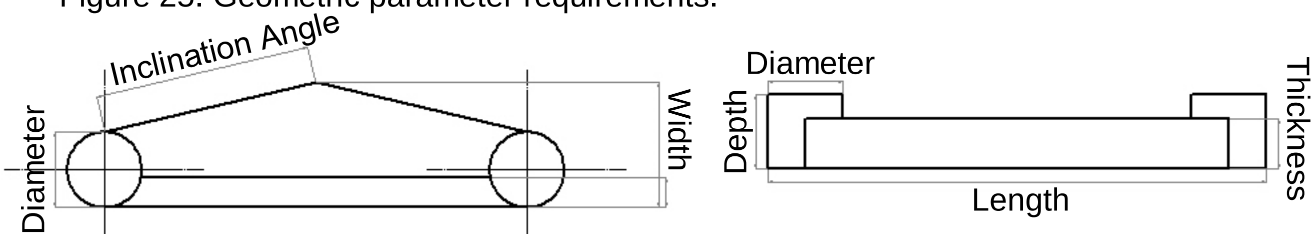
With the classification of the parts by shape and type of injection was possible to obtain the geometric parameter requirements that affect the final shape and that can generate deformations. Finally, the geometric parameter requirements were classified according to the type of figure, taking into account as many parameters as:

- Length

- Width
- Depth
- Inclination angle
- Thickness
- Diameter

The parameters involved in a part directly affect the design of the mold and the injection conditions, that must be taken into account when carrying out the manufacturing process.

Figure 25. Geometric parameter requirements.



Source: *Author.*

The use of CAE modeling systems gives a broad understanding of the plastic micro-parts manufacturing process. Many tools allow simulating the process of injection of plastics, which allows studying the parameters that are involved in the manufacture. The parameters that are directly related to the manufacturing process were taken into account, these were classified as:

Process parameters:

- Filling time.
- Material temperature.
- Mold temperature.
- Maximum injection pressure.
- Limit closing force.

Closing parameters:

- Pressure holding time.
- Refrigeration time.

Mold parameters:

- Injection point.
- Vents.
- Injection channels.

Material parameters:

- Polymer.
- Mold material.

The influence that each type of parameter has on the manufacture of plastic parts was analyzed through tests carried out by CAE systems (see table 15.). The process parameters were taken as a priority as they were the ones that had the greatest influence on the final results.

Table 15. Influence of injection parameters on the formation of plastic parts.

Process parameters:	**Closing parameters:**	**Mold parameters:**	**Material parameters:**
37.4%	14.2%	28.8%	19.6%

Source: *Author, influence analysis by CAE modeling systems.*

With the detection of the parameters that most influences have in the injection processes, the way forward was to identify the most common defects that occur in the manufacture of plastic parts. The use of rapid prototyping tools allows simulate the types of deformations that can occur in the manufacturing process of plastic parts. 3D printing handles materials with similar composition as a plastic injection system would, making it good for studying the negative effects that can occur once the final part is obtained. The types of materials used were classified, giving priority to those for industrial use:

- **ABS.**
- PP.
- Nylon.

The classification of defects was given by the graphic analysis of the resulting parts. The study focused on parts injected with ABS for polymeric characteristics, mechanical characteristics and industrial use that it has. The deformations were classified into groups defined by the geometric failures that the plastic parts may present and in the operating impact (see table 16.).

Table 16. Performance deformation and impact classification.

Type of deformation.	**Definition.**	**Impact rate.**
Sink marks.	Material collapse.	Low.
Flash.	Displacement of joint material.	Medium.
Vacuum venting.	Air accumulations in layers of material.	Low.
Burns.	Temperature Marks on the material.	Medium.
Incomplete parts.	Lack of material to complete the parts.	High.

Source: *Author.*

Through of the qualification of defects, the variables that directly affect the formation of micro plastic parts were related to rapid prototyping parameters. The parameters that are directly involved in the injection process were analyzed, studying and classifying the variables involved in these (see table 17).

Table 17. Classification of parameters according to control variables.

Temperature	**Time**	**Pressure**
Injection molding	**Injection molding**	**Injection molding**
Material temperature.	Filling time.	Maximum injection pressure.
Mold temperature.		Limit closing force.
Rapid prototyping	**Rapid prototyping**	**Rapid prototyping**
Extruder temperature.	Print time.	Extrusion pressure.
Hot bed temperature.		Bonding base.

Source: *Author.*

From the relationship of variables, the level of defect was studied according to the variation of the control parameters, generating an index of relationship between the appearance of defects and the variation of parameters (see table 18).

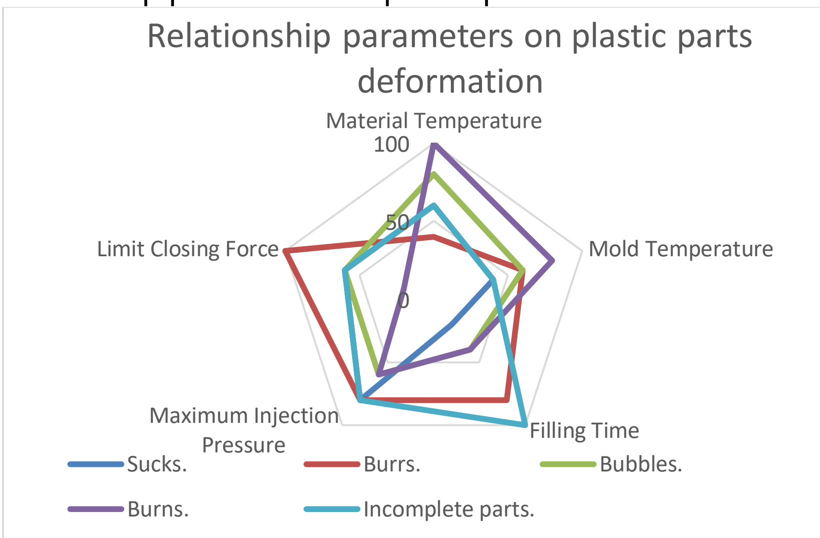
Table 18. Influence level control parameters on plastic parts deformation.

	Material Temperature	**Mold Temperature**	**Filling Time**	**Maximum Injection Pressure**	**Limit Closing Force**
Sink marks.	60 %	40 %	20 %	80 %	60 %
Flash.	40 %	60 %	80 %	80 %	100 %
Vacuum venting.	80 %	60 %	40 %	60 %	60 %
Burns.	100 %	80 %	40 %	60 %	20 %
Incomplete parts.	60 %	40 %	100 %	80 %	60 %

Source: *Author.*

The indices of affectation were determined according to the variation generated on the machine parameters, identifying the relationship levels that are immersed in each parameter according to the type of variable. As a result, the correlation between the control parameters and the plastic defects that arise in the injection process of plastic micro-parts was obtained.

Figure 26. Relationship parameters on plastic parts deformation.



Source: *Author.*

Through the identification of defects and their relationship with injection parameters, an analysis system based on artificial intelligence techniques was designed. Using polynomial regression, a mathematical approach was obtained to the behavior of each of the defects studied with the variation of the control parameters (see table 19.).

Table 19. Mathematical model relation defects-injection parameters.

	Injection Pressure	**Material Temperature**	**Melt Temperature**	**Fill time**	**Injection Volume**
Vacuum venting	$y = 0.0064 \ast x^2 + 0.0101 \ast x - 0.0165$	$y = -0.0035 \ast x^2 + 0.0845 \ast x - 0.0810$	$y = 0.0021 \ast x^2 + 0.0399 \ast x - 0.0420$	$y = -0.0064 \ast x^2 + 0.1485 \ast x - 0.1421$	$y = -0.0073 \ast x^2 + 0.1492 \ast x - 0.1419$
Burns	$y = -0.0070 \ast x^2 + 0.1334 \ast x - 0.1264$	$y = -0.0025 \ast x^2 + 0.0735 \ast x - 0.0710$	$y = -0.0071 \ast x^2 + 0.1394 \ast x - 0.1323$	$y = -0.0033 \ast x^2 + 0.1280 \ast x - 0.1247$	$y = -0.0043 \ast x^2 + 0.0954 \ast x - 0.0911$
Incomplete parts	$y = 0.0047 \ast x^3 - 0.1036 \ast x^2 + 0.7608 \ast x - 0.9482$	$y = -0.0074 \ast x^2 + 0.1672 \ast x - 0.1598$	$y = -0.0131 \ast x^2 + 0.2049 \ast x - 0.1918$	$y = -0.0019 \ast x^2 + 0.1095 \ast x$	$y = 0.0072 \ast x^2 + 0.0272 \ast x - 0.0344$
Flash	$y = -0.0071 \ast x^2 + 0.1578 \ast x - 0.1507$	$y = 0.0021 \ast x^2 + 0.0399 \ast x - 0.0420$	$y = -0.0014 \ast x^2 + 0.1061 \ast x - 0.1047$	$y = 0.0150 \ast x^2 - 0.0924 \ast x - 0.1422$	$y = -0.0067 \ast x^2 + 0.1471 \ast x - 0.1404$
Sink marks	$y = -0.0102 \ast x^2 + 0.1578 \ast x - 0.1507$	$y = -0.0069 \ast x^3 + 0.1386 \ast x^2 - 0.7664 \ast x - 1.2896$	$y = 0.0027 \ast x^2 + 0.0610 \ast x - 0.0637$	$y = 0.0027 \ast x^2 + 0.0610 \ast x - 0.0637$	$y = -0.0073 \ast x^2 + 0.1492 \ast x - 0.1429$

Source: *Author.*

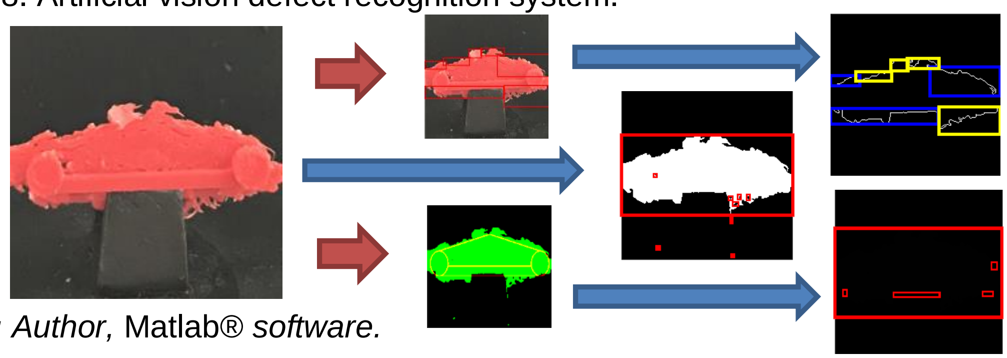
An intelligent system based on fuzzy logic was designed for the ability to take different mathematical models focused on a single variable. For each one of the defects, the mathematical models obtained were taken to work with an inference engine, capable of giving analysis results taking into account each of the behaviors of the variables based on a single defect. The fuzzy logic systems allow the study of how the corresponding variations should be made according to the index of nonconformity against the defect that occurs in the parts.

Figure 27. Fuzzy logical inference engine.

Source: *Author,* Matlab® *software.*

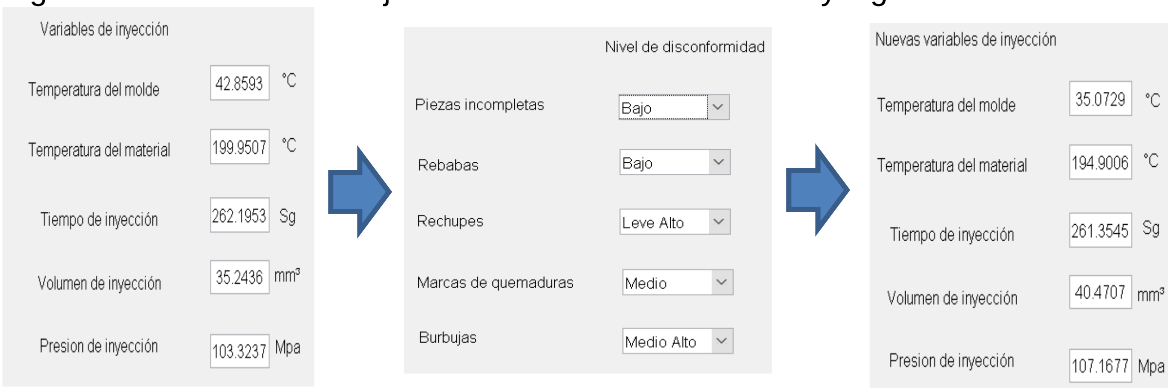
Through artificial vision systems, a defect-recognition code was designed, this is capable to read and interpret the defects presented in the parts resulting from the microinjection process. Each one of the identified analyzes gives a failure index that enters into a fuzzy logic inference engine as an analysis variable to give new injection variables in order to reduce the defects presented.

Figure 28. Artificial vision defect recognition system.



Source: *Author,* Matlab® *software.*

Figure 29. Generation of injection variables based on fuzzy logic.



Loaded injection variables | indicator index of defects | New injection variables generated by the inference eng.

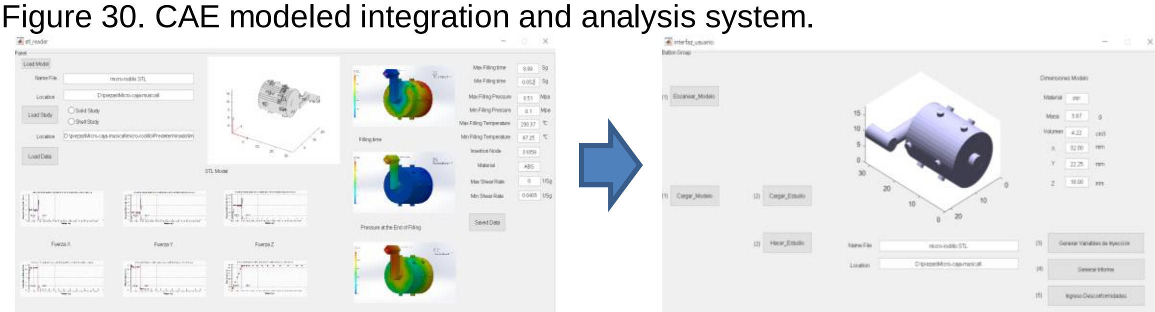
Source: *Author,* Matlab® *software.*

The integration of CAE modeling systems with artificial intelligence systems was developed through a data recognition model loaded from CAD design and CAE simulation software. To read and load data, a file reading system capable of creating a database generated by all the simulations and a neural network-based analysis system capable of interpreting all the data were designed.

The data reading and loading system are capable of interpreting the files generated by the CAE modeling software by loading, analyzing, studying and storing all the parameters that identify the designed part. The system can study and save all the simulation processes that the part designed was subjected (stress tests and injection simulation).

For the reading and interpretation of the stored data, a system based on neural networks was designed. The system can carry out learning interactions to interpret each of the generated data, looking for behavioral patterns based on non-linear regression learning. With the interpretation of the data, the system can give a first option for the parameters of the microinjection plastics process.

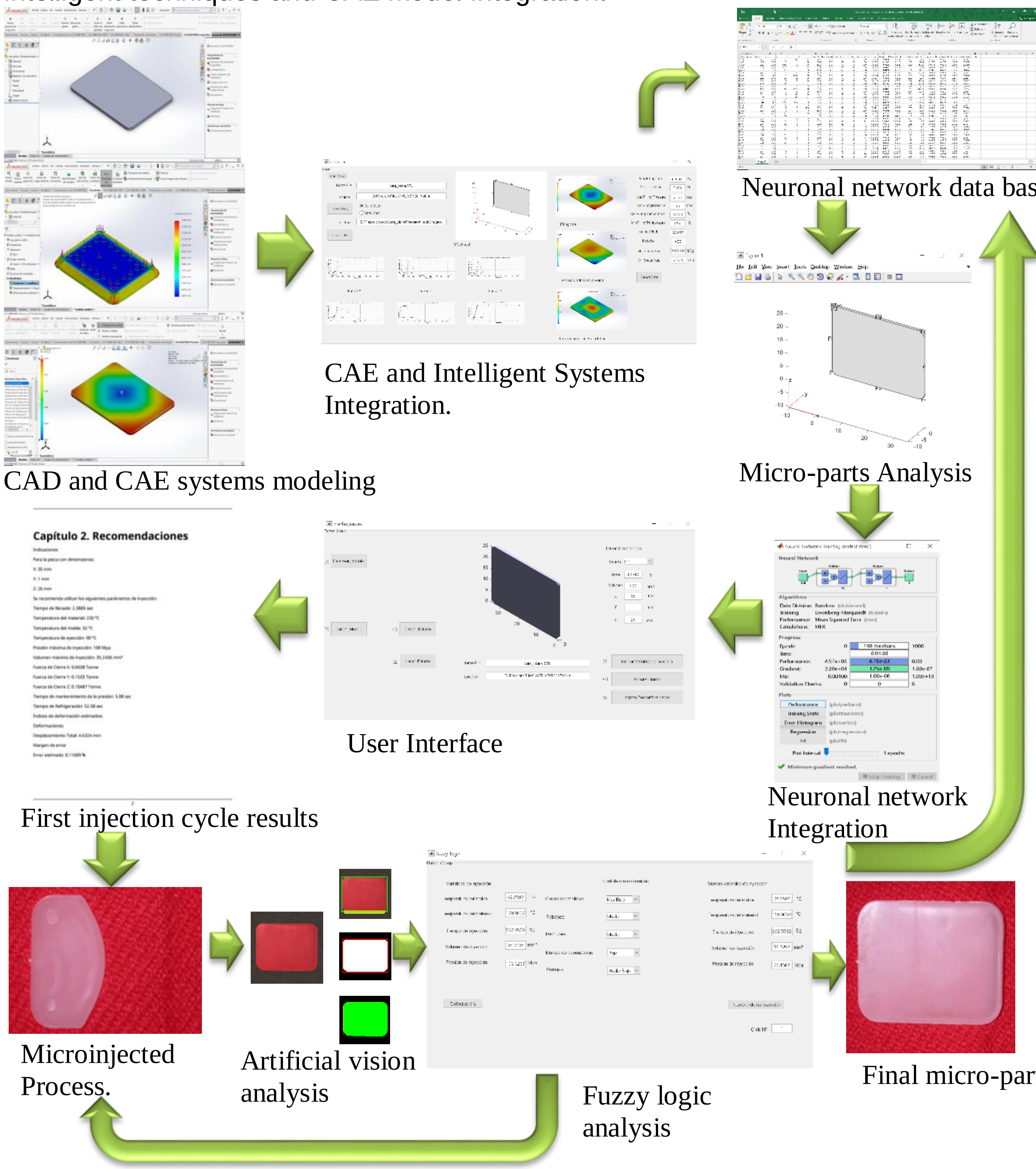
Figure 30. CAE modeled integration and analysis system.



Source: *Author,* Matlab® *software.*

Finally, all the systems were integrated. The analysis and control model for the parameters of the plastic micro-parts injection process were established.

Figure 31. Intelligent system to support micro injection process through artificial intelligent techniques and CAE model integration.



Source: *Author.*

As part of the development and research carried out in this project, two presentations and two articles were presented at the *International Congress of Innovation and Trends in Engineering* "**CONIITI**" V version and at the *Ibero-American Congress of Mechanical Engineering* "**CIBIM**" XIV version; Where the articles ***Integration of CAE modeling and artificial intelligence systems to support manufacturing of plastic micro-parts*** and ***Intelligent System Design for The Micro-manufacturing of Plastics Parts*** were published and exposed.

Integration of CAE modeling and artificial intelligence systems to support manufacturing of plastic micro-parts [96].

"Abstract— Micrometer-scale parts requirements demand an improvement of the development of the micro-manufacturing industry. This fact is due to current technological advances which require small parts with more complex geometrical characteristics, micro-parts with more precise dimensional characteristics, micro-parts with better quality aspect and micro-parts with improved quality operating characteristics. Therefore, the manufacturing processes to obtain high quality microinjection parts is increasingly complicated, requiring much more time (a greater number of cycles) and knowledge from the expert operator, which makes the process unprofitable, as well as highly dependent of the operator and increasing the final costs of microinjection parts for the user. This paper presents the development of an artificial intelligence system based on the integration of CAE modeling, with fuzzy logic techniques and neural networks techniques to support the operator of the injection machine on the selection of optimal machine process parameters to produce good quality micro-parts in fewer process cycles. Tests performed with this intelligent integration system development have demonstrated 30% improvement in the efficiency of injection processes".

Intelligent System Design for The Micromanufacturing of Plastics Parts [97].

"Abstract— The design of plastic parts with characteristics ranging from micrometer to millimeter has become one of the most important needs of today's society, which is constantly seeking to design smaller technological components with a large number of features that allow it to fulfill various tasks, but despite its high demand, the component manufacturing processes are very complex and the probability of failure is very high because the processes are subject to the control of an expert operator. This article provides evidence of the development of software that integrates CAE modeling systems with artificial intelligence systems in order to optimize plastic injection processes to obtain plastic parts in fewer injection cycles, reducing failures and optimizing thus materials, costs and times".

[96] Rojas, A., Chaves, M. L., Bolivar, H., & Vizan, A. (2019). Integration of CAE Modeling and Artificial Intelligence Systems to Support Manufacturing of Plastic Microparts. *2019 Congreso Internacional de Innovacion y Tendencias En Ingenieria, CONIITI 2019 - Conference Proceedings*.

[97] Rojas, A., Chaves, M., & Vizan, A. (2019). INTELLIGENT SYSTEM DESIGN FOR THE MICROMANUFACTURING OF PLASTICS PARTS. *Congreso Iberoamericano de Ingenieria Mecanica, CIBIM CIBEM 2019*. (pp. 96 – 103).

10. VALIDATION OF PROJECT

For the validation of the project, injection tests were performed using the operation of the computer assistance program against injection tests performed by operators. For the tests, 15 parts of micrometric characteristics were used as a basis, with which the verification procedure for detecting defects could be carried out, either by analysis of the operators or by using the artificial vision system.

Analysis tables were made for the tests. These make possible to keep a count of the injection cycles, the injection parameter values and the indices of nonconformity that may occur with respect to defects. (see table 20.).

Table 20. Cycle and defect counter

Cycle No	Injection pressure	Material temperatur	Mold temperatur	Filling time	Injection volume	Bubbles	Burns	Incomplete part	Burrs	Sucks

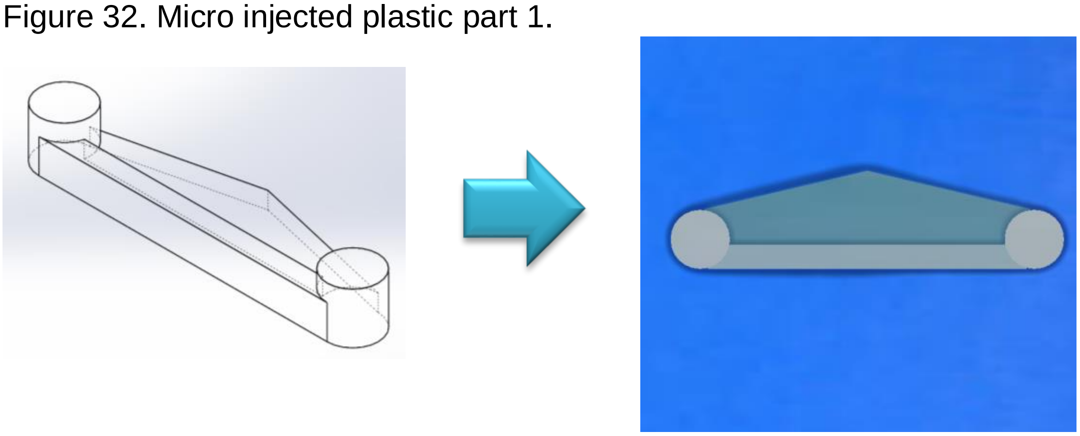
Source: *Author.*

With the adjustment of data and the selection of the parts, the injection tests were carried. With the test, the comparison of results with the use of the system and without the use of it was made.

Result tests for three sample parts:

Micro plastic part 1:

Figure 32. Micro injected plastic part 1.



Source: *Author.*

Injection cycle tests using the expert system are shown below:

Table 21. Cycle and defect counter Micro plastic part 1 (using the system-ABS).

Cycle No	Injection pressure	Material temperature	Mold temperature	Filling time	Injection volume	Bubbles	Burns	Incomplete part	Burrs	Sucks
1	111	219	32.1	13	15.3	2		2		
2	111	225	35	23	15	3				1
3	111	230	32	20	18	2				1
4	115	235	30	18	12		2		5	
5	111	230	30	17	10					

Source: *Author.*

Injection cycle tests without the expert system are shown below:

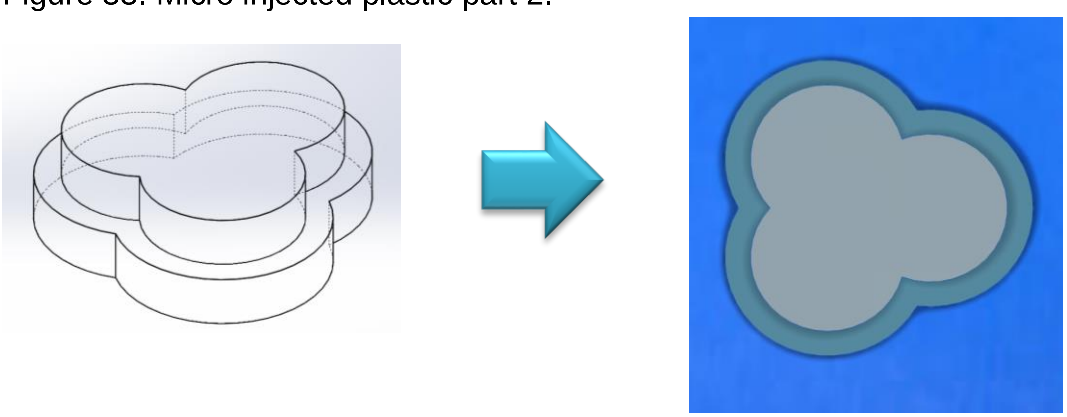
Table 22. Cycle and defect counter Micro plastic part 1 (without the system-ABS).

Cycle No	Injection pressure	Material temperature	Mold temperature	Filling time	Injection volume	Bubbles	Burns	Incomplete part	Burrs	Sucks
1	111	219	32.1	13	15.3	2		2		
2	111	225	35	23	15	3				1
3	112	228	40	26	15	3	2		2	4
4	114	230	38	22	20	4	1		3	3
5	110	230	32	20	18	2				1
6	111	235	30	18	12		2		2	
7	111	230	31	15	8			1		
8	111	230	30	17	10					

Source: *Author.*

Micro plastic part 2:

Figure 33. Micro injected plastic part 2.



Source: *Author.*

Injection cycle tests using the expert system are shown below:

Table 23. Cycle and defect counter Micro plastic part 2 (using the system-ABS).

Cycle No	Injection pressure	Material temperature	Mold temperature	Filling time	Injection volume	Bubbles	Burns	Incomplete part	Burrs	Sucks
1	100.3	218.55	32.26	1.38	35.26	2	2	4		
2	105	218	32	10	35	2	1	3		1
3	111	215	30	15	32	1	1	1		
4	111	210	30	17	32.5					

Source: *Author.*

Injection cycle tests without the expert system are shown below:

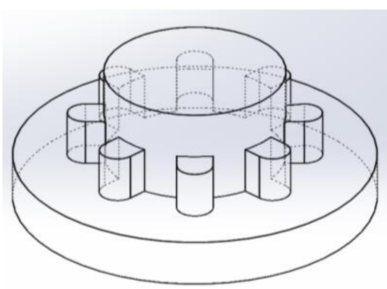
Table 24. Cycle and defect counter Micro plastic part 2 (without the system-ABS).

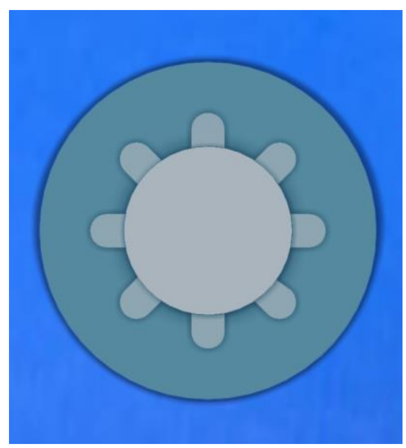
Cycle No	Injection pressure	Material temperature	Mold temperature	Filling time	Injection volume	Bubbles	Burns	Incomplete part	Burrs	Sucks
1	100.3	218.55	32.26	1.38	35.26	2	2	4		
2	105	218	32	10	35	2	1	3		1
3	110	220	28	20	32	1	1		2	2
4	111	215	30	15	33	1	1	1		
5	110	212	32	16	32	2				1
6	111	210	30	17	32.5					

Source: *Author.*

Micro plastic part 3:

Figure 34. Micro injected plastic part 3.





Source: *Author.*

Injection cycle tests using the expert system are shown below:

Table 25. Cycle and defect counter Micro plastic part 3 (using the system-ABS).

Cycle No	Injection pressure	Material temperature	Mold temperature	Filling time	Injection volume	Bubbles	Burns	Incomplete part	Burrs	Sucks
1	99	220	32	0.96	35.74		2	4		3
2	99	215	32	4.7	25.4		1	2		2
3	98	210	32	10	19					1
4	98	210	30	10	17					

Source: *Author.*

Injection cycle tests without the expert system are shown below:

Table 26. Cycle and defect counter Micro plastic part 3 (without the system-ABS).

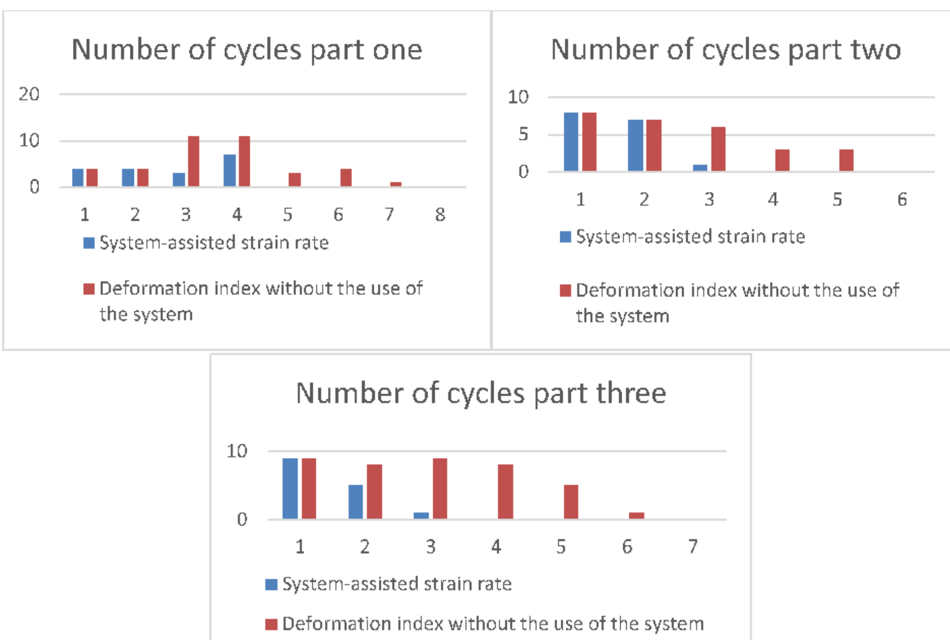
Cycle No	Injection pressure	Material temperature	Mold temperature	Filling time	Injection volume	Bubbles	Burns	Incomplete part	Burrs	Sucks
1	99	220	32	0.96	35.74		2	4		3
2	99	200	26	20	30				5	3
3	110	217	34	3	20	2	2	3		2
4	105	215	32	4	25	2	1	3		2
5	99	215	32	4.7	25		1	2		2
6	98	210	32	10	19					1
7	98	210	30	10	17					

Source: *Author.*

The complete tables of results for the injection process of the fifteen test parts are shown in the annexes.

Through the injection tests, a comparison between the use of the system and the tests carried out by operators was made for each of the parts, studying the deformation indexes that emerged with respect to each injection cycle. For each one of the parts was determined that the reduction of deformations is more linear and controlled with the use of the analysis system than without the use of it. Using the system was also found that is possible to reduce the number of injection cycles necessary to produce a quality part. The results of the analysis of purchases are shown below.

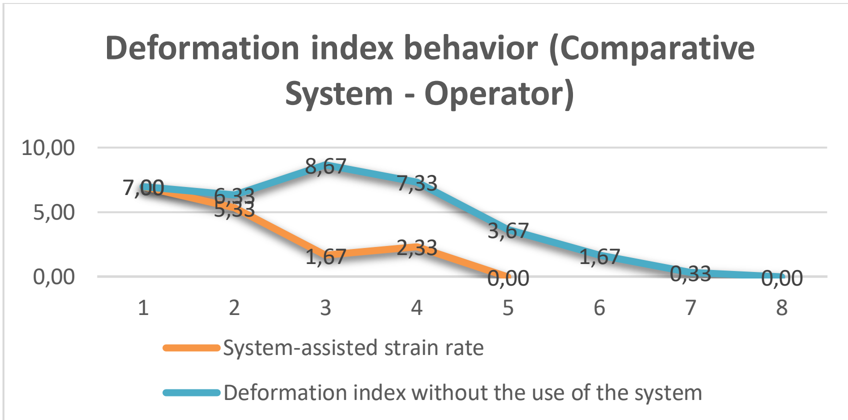
Figure 35. Comparison of injection cycles parts one, two and three.



Source: *Author.*

With the use of the system is demonstrated how the deformation indexes are reduced in a more linear way, which allows to better control in deformation reduction and thus reduce the injection cycles necessary for an optimal part.

Figure 36. Deformation index behavior.



Source: *Author.*

Table 27. Cycle and defect counter Micro plastic part (ABS).

Injected parts	Percentage deformation rates operator control.	Injection cycles required operator control.	Percentage deformation indices control assisted by the system.	Injection cycles required control assisted by the system.
1	9,50%	8	7,20%	5
2	9,00%	6	9,00%	4
3	11,43%	7	7,50%	4
4	10,86%	7	6,00%	5
5	10,00%	8	14,00%	3
6	10,00%	6	3,50%	4
7	10,00%	9	4,40%	5
8	9,14%	7	5,00%	6
9	10,00%	5	6,00%	4
10	10,86%	7	5,60%	5
11	9,56%	9	7,60%	5
12	11,75%	8	8,50%	4
13	10,67%	6	9,33%	3
14	11,14%	7	8,00%	4
15	10,75%	8	9,00%	4

Source: *Author.*

Table 28. Cycle and defect counter Micro plastic part (PP).

Injected parts	Percentage deformation rates operator control.	Injection cycles required	Percentage deformation indices control assisted by the system.	Injection cycles required
1	9,00%	5	15,20%	4
2	18,00%	4	13,50%	2
3	10,00%	5	13,33%	3
4	10,00%	4	15,20%	3
5	10,50%	5	11,43%	4
6	4,67%	5	10,00%	3
7	11,00%	6	11,25%	2
8	10,00%	5	10,67%	3
9	6,00%	4	10,00%	4
10	14,00%	5	19,00%	2
11	12,67%	6	14,33%	3
12	11,33%	5	13,43%	3
13	7,00%	4	12,80%	4
14	16,00%	5	15,60%	2
15	12,00%	6	21,50%	3

Source: *Author.*

For the injected parts was determined that the average of injection cycles necessary to obtain a quality part using the system are four cycles approximately, in comparison with the necessary cycles performed by an operator that are seven cycles approximately. Below is the analysis of results and the calculation of percentage improvement that occurs with the use of the system.

Improvement of the cycles necessary in the injection process:

$$OpSEnABS = 100\% - \frac{\frac{1}{ns}\sum_{i=1}^{ns} Xvs * 100\%}{\frac{1}{no}\sum_{i=1}^{no} Xvo} = 100 - \frac{4.33 * 100}{7.2} = 39.81\%$$

$$OpSEnPP = 100\% - \frac{\frac{1}{ns}\sum_{i=1}^{ns} Xvs * 100\%}{\frac{1}{no}\sum_{i=1}^{no} Xvo} = 100 - \frac{3 * 100}{4.93} = 39.14\%$$

Reduction of the deformation indexes that occur for each cycle of injection:

$$OpSEiABS = 100\% - \frac{\frac{1}{ns}\sum_{i=1}^{ns} Xis * 100\%}{\frac{1}{no}\sum_{i=1}^{no} Xio} = 100 - \frac{7.38 * 100}{10.31} = 28.46\%$$

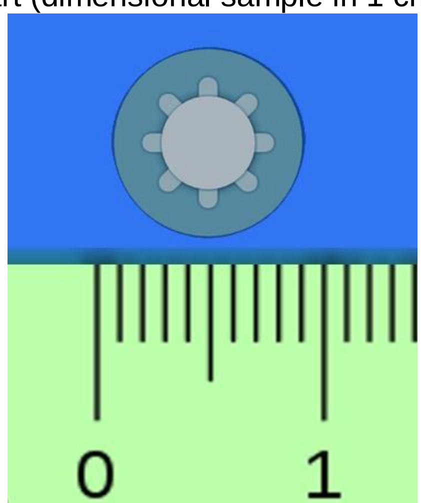
$$OpSEiPP = 100\% - \frac{\frac{1}{ns}\sum_{i=1}^{ns} Xis * 100\%}{\frac{1}{no}\sum_{i=1}^{no} Xio} = 100 - \frac{10.81 * 100}{15.08} = 28.31\%$$

The values handled were obtained by statistical analysis in Table 27 and Table 28.

With the tests carried out is determined that by making the system an improvement of 39.81% to ABS and 39.14% to PP of the cycles necessary in the injection process is seen, in addition to a reduction of 28.46%to ABS and 28.31% to PP of the deformation indexes that occur for each cycle of injection in order to obtain a part of optimum quality.

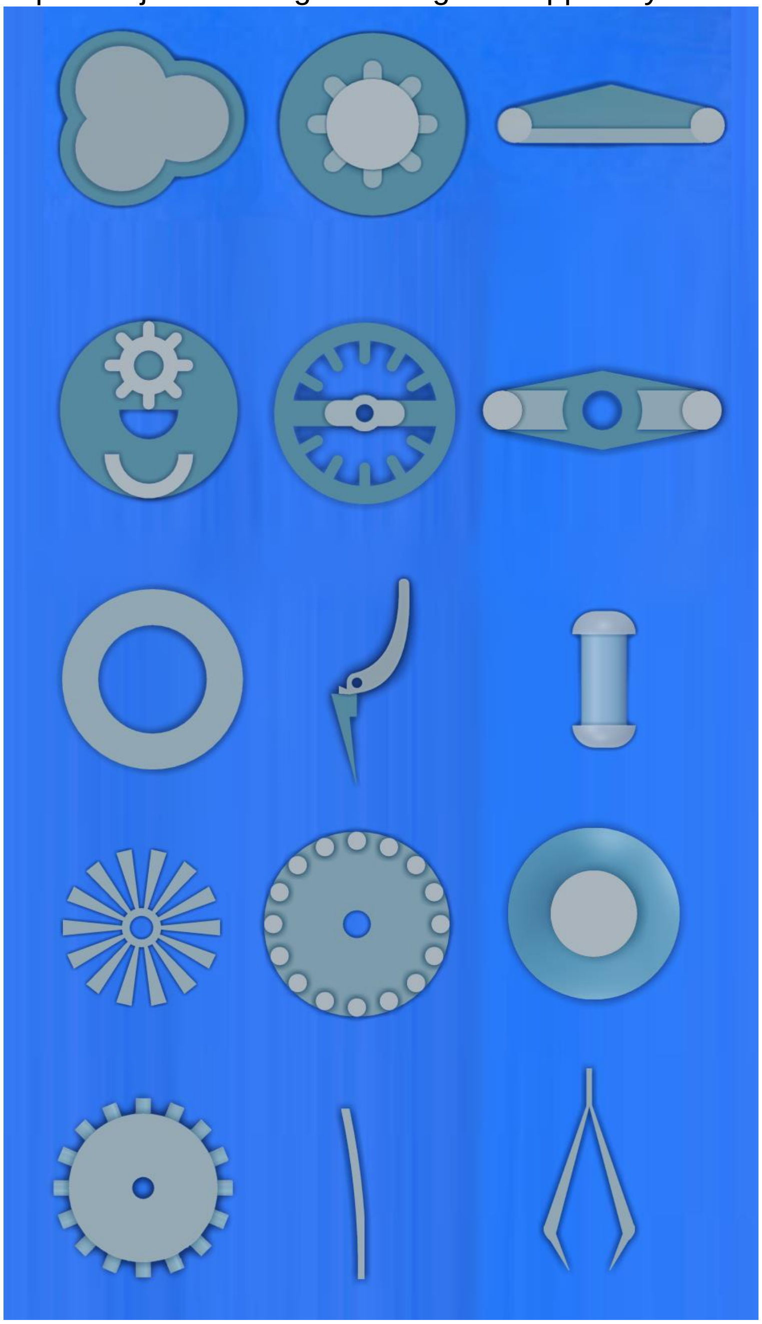
The results and analysis shown in this document demonstrate the development, implementation and operation of the **Intelligent System to Support Micro Injection Process Through Artificial Intelligent Techniques and CAE Model Integration.**

Figure 37. Micro plastic part (dimensional sample in 1 cm.).



Source: *Author.*

Figure 38. Micro parts injected using the designed support system.



Source: *Author.*

11. CONCLUSIONS AND FUTURE WORKS

CAE designs were made of thirty different parts with micrometric characteristics which were subjected to six geometric variations each one. With the designs made, the geometric requirements were classified in length, width, depth, inclination angle, Diameter and thickness depending or type or part. The geometric parameter requirements were generalized determining the optimal design characteristics to produce standard parts.

Geometric variables influence the quality of the parts by being directly related to the design of the molds, with a 28.8% of influence in the final result of the parts involves. The geometric requirements were determined and established, searching for designs of standard geometric shapes that were possible to manufacture in the design of the molds.

Behavioral studies were carried out for different plastic materials, finding an influence of 19.6% in the result of fabrication of the final part The tests were carried out on materials that use injection molding manufacturing, focusing on the use of ABS and polypropylene due to their industrial and mechanical characteristics. ABS was determined like primary material to its compression properties that allow obtain better results in the final quality of the parts.

An index of influence of 37.4% of the machine variables on the quality of the final part was determined. Filling time, Material temperature, Mold temperature. Maximum injection pressure and Injection Volume were established as main parameters, focusing the analyzes and studies on the control of the variables involved in these.

With rapid prototyping tests. material deformation analyzes were carried out, identifying the types of defects classified in Flash, Sink marks, Vacuum venting, burns and incomplete parts. The use of rapid prototyping systems allowed analyzing the geometries of the designed parts, studying how the defects occurs affects the results and the operation of the resulting parts.

The use of artificial vision allowed the identification of areas of interest, in order to recognize geometries through of depth analysis and the conversion of pixels into dimensions. These systems also served as support in the detection of defects, recognizing the affected areas, determining error rates and levels of nonconformity.

For the graphic analysis of micro-plastic parts through of artificial vision, a very high-resolution camera with the ability to capture all the details in an image is necessary. When handling millimeter and micrometer parts, these have very low-dimensional geometries that are difficult to see, so also to study and analyses. In this way, a high-resolution camera capable of capturing in pixels each of the details present in a part was implemented.

Neural network systems allowed to standardize all the studies carried out, making interactions between data in order to obtain a relationship between them, looking for the optimal values that fit the designed parts. Through the interaction of data and the use of the database, a wide range system was achieved, capable of giving optimum values to diverse parts with different geometric characteristics.

The neural network systems used in industrial processes such as the microinjection of plastics allow to analyze, standardize and determine the behavior of the systems from the study and learning of the different sub-processes involved. The management of diverse and extensive databases obtained by the storage of variables, facilitates the learning of neural network systems, achieving an intelligent system with experience and intuition capable of approaching the knowledge and instinct of an expert operator.

Through Polynomial regression method, the relationships between the control variables and the presence of defects were determined. The use of the database and the interaction between variables and defects, allow studying the behavior that occurred with the variation of the control variables, establishing by polynomial regression as mathematical model that give a 'relationship between each type of defect with the parameters of machine.

The use of fuzzy logic systems allowed to establish inference engines, facilitating the rectification of the variables generated by the neural networks in each injection cycle. Using inference engines powered by mathematical models determined by polynomial regression was possible to correct defects generated by external parameters that cannot be determined by neural networks, but which also affect the final results in the quality of the designed parts.

The integration of CAE modeling systems with intelligent systems allows improving the efficiency of the production process of micro plastic parts by injection molding. The use of the system determined a 39.81% improvement in the number of production cycles required with ABS and 39.14% improvement in the number of production cycles required with PP, compared to a traditional manufacturing process, where intelligent systems are not used.

With the reduction in the injection cycles necessary to produce a quality part, partial elimination of time and material uses is evidenced, eliminating the waste material required to achieve an optimal part. This reduction contributed to the decrease in the environmental impact.

The use of the intelligent systems allows a controlled behavior on the variations necessary to obtain a quality part, giving a reduction in the presence of defects of 28.46% with ABS and 28.31% to PP in the injection cycles, thus giving more linear control over the variables and the presence of defects.

The uses of the Intelligent system to support the microinjection process through artificial intelligent techniques and CAE model integration allows reduces the loss of materials and time in the micro-injection manufacture process; This makes possible better profitability in the efficiency of the process, giving bigger feasibility of micro-parts manufacture in the national industry.

The use of the intelligent system designed as a support software in the microinjection process is an innovative method that opens the possibilities of expansion and application in the national industry. The use of intelligent systems allows improving the efficiency of processes, reducing production times and material consumption, without the need to resort to highly experienced operators, which facilitates control over machinery and creates new opportunities for operators with little experience or in the formation process.

As a result of the work carried out, three scientific articles were developed together with two presentations at engineering conferences. The development of the article "*INTEGRATION OF CAE MODELING AND ARTIFICIAL INTELLIGENCE SYSTEMS TO SUPPORT MANUFACTURING OF PLASTIC MICRO-PARTS*" was published and presented at the *international congress of innovation and trends in engineering* "CONIITI", V version, in the year 2019; The development of the article "*INTELLIGENT SYSTEM DESIGN FOR THE MICROFABRICATION OF PLASTICS*" was published and presented at the *Ibero-American Congress of Mechanical Engineering* "CIBIM" XIV version, in the year 2019. Finally, the article "COMPUTATIONAL INTELLIGENCE SYSTEM APPLIED AT PLASTIC MICROPARTS MANUFACTURING PROCESS " was presented to the *International Journal of Grid and Utility Computing* which has been accepted to revision process.

As future works, the possibility of deepening the development of more complex systems focused on different parameters involved in injection processes, such as mold design, other material test, non-conventional geometries studies. The implementation of intelligent systems as support for industrial processes has a wide field of application, which opens different possibilities to deepen the development of Intelligent systems, deepening applications such as the use of artificial vision systems, big data management, predictive control systems, among many others.

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13. ANNEXES

Annex 1. Tests carried out with CAE systems.

Thirty micro parts designed.

Database of geometric variations and injection parameters of diverse micro parts provided by CAE analysis.

Material	Volume	Mass	X	Y	Z	Filling time	Material temperature	Mold temperature	Ejection temperature	Pressure
ABS	0,24	0,27	14	6,1	14	0,41	230	50	90	100
ABS	0,5	0,55	20	6	20	0,45	230	50	90	100
ABS	0,31	0,34	9,96	5	9,96	1,01	230	50	90	100
ABS	0,05	0,05	4,73	5	4,5	0,26	230	50	90	100
ABS	0,07	0,08	20	3	3	1,03	230	50	90	100
ABS	1,84	2,03	7	20	20	3,29	230	50	90	100
ABS	0,72	0,8	5	19,94	20	0,54	230	50	90	100
ABS	1,32	1,45	20	20	20	2,19	230	50	90	100
ABS	1,84	2,03	7	20	20	3,29	230	50	90	100
ABS	1,62	1,78	24	5	24	2,58	230	50	90	100
ABS	1,48	1,63	20	20	20	0,22	230	50	90	100
ABS	4,22	4,65	32	22,25	18	8,86	230	50	90	100
ABS	0,78	0,86	2	20	20	1,49	230	50	90	100
ABS	0,01	0,01	1	1,4	10	0,1	230	50	90	100
ABS	0	0	3	1,4	1,4	0,09	230	50	90	100
ABS	0,05	0,05	7,56	2	20,02	0,26	230	50	90	100
ABS	0,18	0,2	9,92	9,77	5	0,74	230	50	90	100
ABS	0,17	0,19	20	2	5	0,71	230	50	90	100
ABS	0,01	0,01	1	20	4,38	0,12	230	50	90	100
ABS	0,26	0,28	8	8	8	1,63	230	50	90	100
ABS	1,4	1,55	40	10	40	0,49	230	50	90	100
ABS	0,84	0,93	24	10	24	0,69	230	50	90	100
ABS	0,92	1,01	10	15	20	3,91	230	50	90	100
PP	0,28	0,25	20	3	5	0,62	230	30	95	111
PP	0,28	0,25	20	3	5	0,62	150	20	95	5
PP	0,28	0,25	20	3	5	0,62	230	20	95	5
PP	0,28	0,25	20	3	5	0,62	230	20	95	5
PP	0,28	0,25	20	3	5	0,62	230	50	95	98
PP	0,28	0,25	20	3	5	0,62	230	20	95	98
PP	0,28	0,25	20	3	5	0,62	230	30	95	98
PP	0,28	0,25	20	3	5	0,62	230	30	95	1,3
PP	0,28	0,25	20	3	5	0,68	230	50	90	5
PP	0,04	0,04	6	2	6	0,42	230	50	95	100
PP	0,04	0,04	6	2	6	0,54	150	20	80	5
PP	0,04	0,04	6	2	6	0,54	230	20	95	5

PP	0,04	0,04	6	2	6	0,54	230	20	95	128
PP	0,04	0,04	6	2	6	0,54	243	20	95	98
PP	0,04	0,04	6	2	6	0,54	230	20	95	111
PP	0,04	0,04	6	2	6	0,54	230	20	95	128
PP	0,05	0,04	6	3	6	0,35	230	50	95	100
PP	0,5	0,45	20	6	20	0,45	230	50	95	100
PP	0,05	0,04	4,73	5	4,5	0,26	230	50	95	100
PP	0,31	0,28	9,96	5	9,96	1,02	230	50	95	100
PP	0,07	0,07	20	3	3	1,05	230	50	95	100
PP	1,32	1,21	20	20	20	2,15	230	50	95	100
PP	0,72	0,66	5	19,94	20	0,54	230	50	95	100
PP	1,3	1,19	20	24	20	0,58	230	50	95	100
PP	1,84	1,69	7	20	20	3,43	230	50	95	100
PP	4,22	3,87	32	22,25	18	9	230	50	95	100
PP	0,24	0,27	14	6,1	14	0,41	230	50	90	100
PP	0,5	0,55	20	6	20	0,45	230	50	90	100
PP	0,31	0,34	9,96	5	9,96	1,01	230	50	90	100
PP	0,05	0,05	4,73	5	4,5	0,26	230	50	90	100
PP	0,07	0,08	20	3	3	1,03	230	50	90	100
PP	1,84	2,03	7	20	20	3,29	230	50	90	100
PP	0,72	0,8	5	19,94	20	0,54	230	50	90	100
PP	1,32	1,45	20	20	20	2,19	230	50	90	100
PP	1,84	2,03	7	20	20	3,29	230	50	90	100
ABS	0,24	0,27	14	6,1	14	0,41	230	50	90	100
ABS	0,5	0,55	20	6	20	0,45	230	50	90	100
ABS	0,31	0,34	9,96	5	9,96	1,01	230	50	90	100
ABS	0,05	0,05	4,73	5	4,5	0,26	230	50	90	100
ABS	0,07	0,08	20	3	3	1,03	230	50	90	100
ABS	1,84	2,03	7	20	20	3,29	230	50	90	100
ABS	0,72	0,8	5	19,94	20	0,54	230	50	90	100
ABS	1,32	1,45	20	20	20	2,19	230	50	90	100
ABS	1,84	2,03	7	20	20	3,29	230	50	90	100
ABS	1,62	1,78	24	5	24	2,58	230	50	90	100
ABS	1,48	1,63	20	20	20	0,22	230	50	90	100
ABS	4,22	4,65	32	22,25	18	8,86	230	50	90	100
ABS	0,78	0,86	2	20	20	1,49	230	50	90	100
ABS	0,01	0,01	1	1,4	10	0,1	230	50	90	100
ABS	0	0	3	1,4	1,4	0,09	230	50	90	100

ABS	0,05	0,05	7,56	2	20,02	0,26	230	50	90	100
ABS	0,18	0,2	9,92	9,77	5	0,74	230	50	90	100
ABS	0,17	0,19	20	2	5	0,71	230	50	90	100
ABS	0,01	0,01	1	20	4,38	0,12	230	50	90	100
ABS	0,26	0,28	8	8	8	1,63	230	50	90	100
ABS	1,4	1,55	40	10	40	0,49	230	50	90	100
ABS	0,84	0,93	24	10	24	0,69	230	50	90	100
ABS	0,92	1,01	10	15	20	3,91	230	50	90	100
PP	1,62	1,78	24	5	24	2,58	230	50	90	100
PP	1,48	1,63	20	20	20	0,22	230	50	90	100
PP	4,22	4,65	32	22,25	18	8,86	230	50	90	100
PP	0,78	0,86	2	20	20	1,49	230	50	90	100
PP	0,01	0,01	1	1,4	10	0,1	230	50	90	100
PP	0	0	3	1,4	1,4	0,09	230	50	90	100
PP	0,05	0,05	7,56	2	20,02	0,26	230	50	90	100
PP	0,18	0,2	9,92	9,77	5	0,74	230	50	90	100
PP	0,17	0,19	20	2	5	0,71	230	50	90	100
PP	0,01	0,01	1	20	4,38	0,12	230	50	90	100
PP	0,26	0,28	8	8	8	1,63	230	50	90	100
PP	1,4	1,55	40	10	40	0,49	230	50	90	100
PP	0,84	0,93	24	10	24	0,69	230	50	90	100
PP	0,92	1,01	10	15	20	3,91	230	50	90	100
PP	0,28	0,25	20	3	5	0,62	230	30	95	111
PP	0,28	0,25	20	3	5	0,62	150	20	95	5
PP	0,28	0,25	20	3	5	0,62	230	20	95	5
PP	0,28	0,25	20	3	5	0,62	230	20	95	5
PP	0,28	0,25	20	3	5	0,62	230	50	95	98
PP	0,28	0,25	20	3	5	0,62	230	20	95	98
PP	0,28	0,25	20	3	5	0,62	230	30	95	98
PP	0,28	0,25	20	3	5	0,62	230	30	95	1,3
PP	0,28	0,25	20	3	5	0,68	230	50	90	5
PP	0,04	0,04	6	2	6	0,42	230	50	95	100
PP	0,04	0,04	6	2	6	0,54	150	20	80	5
PP	0,04	0,04	6	2	6	0,54	230	20	95	5
PP	0,04	0,04	6	2	6	0,54	230	20	95	128
ABS	0,24	0,27	14	6,1	14	0,41	230	50	90	100
ABS	0,5	0,55	20	6	20	0,45	230	50	90	100
ABS	0,31	0,34	9,96	5	9,96	1,01	230	50	90	100
ABS	0,05	0,05	4,73	5	4,5	0,26	230	50	90	100

ABS	0,07	0,08	20	3	3	1,03	230	50	90	100
ABS	1,84	2,03	7	20	20	3,29	230	50	90	100
ABS	0,72	0,8	5	19,94	20	0,54	230	50	90	100
ABS	1,32	1,45	20	20	20	2,19	230	50	90	100
ABS	1,84	2,03	7	20	20	3,29	230	50	90	100
ABS	1,62	1,78	24	5	24	2,58	230	50	90	100
ABS	1,48	1,63	20	20	20	0,22	230	50	90	100
ABS	4,22	4,65	32	22,25	18	8,86	230	50	90	100
ABS	0,78	0,86	2	20	20	1,49	230	50	90	100
ABS	0,01	0,01	1	1,4	10	0,1	230	50	90	100
ABS	0	0	3	1,4	1,4	0,09	230	50	90	100
ABS	0,05	0,05	7,56	2	20,02	0,26	230	50	90	100
ABS	0,18	0,2	9,92	9,77	5	0,74	230	50	90	100
ABS	0,17	0,19	20	2	5	0,71	230	50	90	100
ABS	0,01	0,01	1	20	4,38	0,12	230	50	90	100
ABS	0,26	0,28	8	8	8	1,63	230	50	90	100
ABS	1,4	1,55	40	10	40	0,49	230	50	90	100
ABS	0,84	0,93	24	10	24	0,69	230	50	90	100
ABS	0,92	1,01	10	15	20	3,91	230	50	90	100
PP	0,04	0,04	6	2	6	0,54	243	20	95	98
PP	0,04	0,04	6	2	6	0,54	230	20	95	111
PP	0,04	0,04	6	2	6	0,54	230	20	95	128
PP	0,05	0,04	6	3	6	0,35	230	50	95	100
PP	0,5	0,45	20	6	20	0,45	230	50	95	100
PP	0,05	0,04	4,73	5	4,5	0,26	230	50	95	100
PP	0,31	0,28	9,96	5	9,96	1,02	230	50	95	100
PP	0,07	0,07	20	3	3	1,05	230	50	95	100
PP	1,32	1,21	20	20	20	2,15	230	50	95	100
PP	0,72	0,66	5	19,94	20	0,54	230	50	95	100
PP	1,3	1,19	20	24	20	0,58	230	50	95	100
PP	1,84	1,69	7	20	20	3,43	230	50	95	100
PP	4,22	3,87	32	22,25	18	9	230	50	95	100
PP	4,22	3,87	32	22,25	18	9	230	50	95	100
PP	0,24	0,27	14	6,1	14	0,41	230	50	90	100
PP	0,5	0,55	20	6	20	0,45	230	50	90	100
PP	0,31	0,34	9,96	5	9,96	1,01	230	50	90	100
PP	0,05	0,05	4,73	5	4,5	0,26	230	50	90	100
PP	0,07	0,08	20	3	3	1,03	230	50	90	100

PP	1,84	2,03	7	20	20	3,29	230	50	90	100
PP	0,72	0,8	5	19,94	20	0,54	230	50	90	100
PP	1,32	1,45	20	20	20	2,19	230	50	90	100
PP	1,84	2,03	7	20	20	3,29	230	50	90	100
PP	1,62	1,78	24	5	24	2,58	230	50	90	100
PP	1,48	1,63	20	20	20	0,22	230	50	90	100
PP	4,22	4,65	32	22,25	18	8,86	230	50	90	100
PP	0,78	0,86	2	20	20	1,49	230	50	90	100
PP	0,01	0,01	1	1,4	10	0,1	230	50	90	100
PP	0	0	3	1,4	1,4	0,09	230	50	90	100
PP	0,05	0,05	7,56	2	20,02	0,26	230	50	90	100
PP	0,18	0,2	9,92	9,77	5	0,74	230	50	90	100
PP	0,17	0,19	20	2	5	0,71	230	50	90	100
PP	0,01	0,01	1	20	4,38	0,12	230	50	90	100
PP	0,26	0,28	8	8	8	1,63	230	50	90	100
PP	1,4	1,55	40	10	40	0,49	230	50	90	100
PP	0,84	0,93	24	10	24	0,69	230	50	90	100
PP	0,92	1,01	10	15	20	3,91	230	50	90	100
PP	0,28	0,25	20	3	5	0,62	230	30	95	111
PP	0,28	0,25	20	3	5	0,62	150	20	95	5
PP	0,28	0,25	20	3	5	0,62	230	20	95	5
PP	0,28	0,25	20	3	5	0,62	230	20	95	5
PP	0,28	0,25	20	3	5	0,62	230	50	95	98
PP	0,28	0,25	20	3	5	0,62	230	20	95	98
PP	0,28	0,25	20	3	5	0,62	230	30	95	98
PP	0,28	0,25	20	3	5	0,62	230	30	95	1,3
PP	0,28	0,25	20	3	5	0,68	230	50	90	5
PP	0,04	0,04	6	2	6	0,42	230	50	95	100
PP	0,04	0,04	6	2	6	0,54	150	20	80	5
PP	0,04	0,04	6	2	6	0,54	230	20	95	5
PP	0,04	0,04	6	2	6	0,54	230	20	95	128
PP	0,04	0,04	6	2	6	0,54	243	20	95	98
PP	0,04	0,04	6	2	6	0,54	230	20	95	111
PP	0,04	0,04	6	2	6	0,54	230	20	95	128
PP	0,05	0,04	6	3	6	0,35	230	50	95	100
PP	0,5	0,45	20	6	20	0,45	230	50	95	100
PP	0,05	0,04	4,73	5	4,5	0,26	230	50	95	100
PP	0,31	0,28	9,96	5	9,96	1,02	230	50	95	100
PP	0,07	0,07	20	3	3	1,05	230	50	95	100

PP	1,32	1,21	20	20	20	2,15	230	50	95	100
PP	0,72	0,66	5	19,94	20	0,54	230	50	95	100
PP	1,3	1,19	20	24	20	0,58	230	50	95	100
PP	1,84	1,69	7	20	20	3,43	230	50	95	100
PP	4,22	3,87	32	22,25	18	9	230	50	95	100

Plastic displacement analysis in micro parts provided by CAE analysis.

X Displacement	Y Displacement	Z Displacement	Total Displacement
0,1219	0,1157	0,0827	0,0651
0,1855	0,1579	0,068	0,0955
0,0974	0,0978	0,0554	0,0512
0,0342	0,0315	0,0379	0,0259
0,1482	0,0272	0,0282	0,075
0,0825	0,2648	0,2612	0,1357
0,0552	0,1953	0,1832	0,1008
0,1491	0,1484	0,1994	0,1265
0,0825	0,2648	0,2612	0,1357
0,3021	0,2966	0,0755	0,1531
0,0821	0,1513	0,1508	0,1009
0,3532	0,2202	0,2469	0,2254
0,024	0,1662	0,172	0,1018
0,0142	0,0456	0,0168	0,0256
0,0274	0,0112	0,0118	0,0156
0,0625	0,1235	0,0301	0,0705
0,0912	0,0524	0,0885	0,0484
0,1715	0,0489	0,0445	0,0903
0,0166	0,0916	0,0823	0,0774
0,1012	0,1011	0,1086	0,0575
0,2366	0,2441	0,0796	0,1387
0,1483	0,146	0,0891	0,0834
0,1277	0,2315	0,1993	0,1437
0,0083	0,0114	0,0053	0,0082
0,0906	0,0333	0,0302	0,0464
0,152	0,0649	0,056	0,079
0,152	0,0649	0,056	0,079
0,162	0,0638	0,0547	0,0837
0,0083	0,0123	0,0074	0,0099
0,0095	0,0142	0,0081	0,0114
0,0082	0,0122	0,0072	0,0096

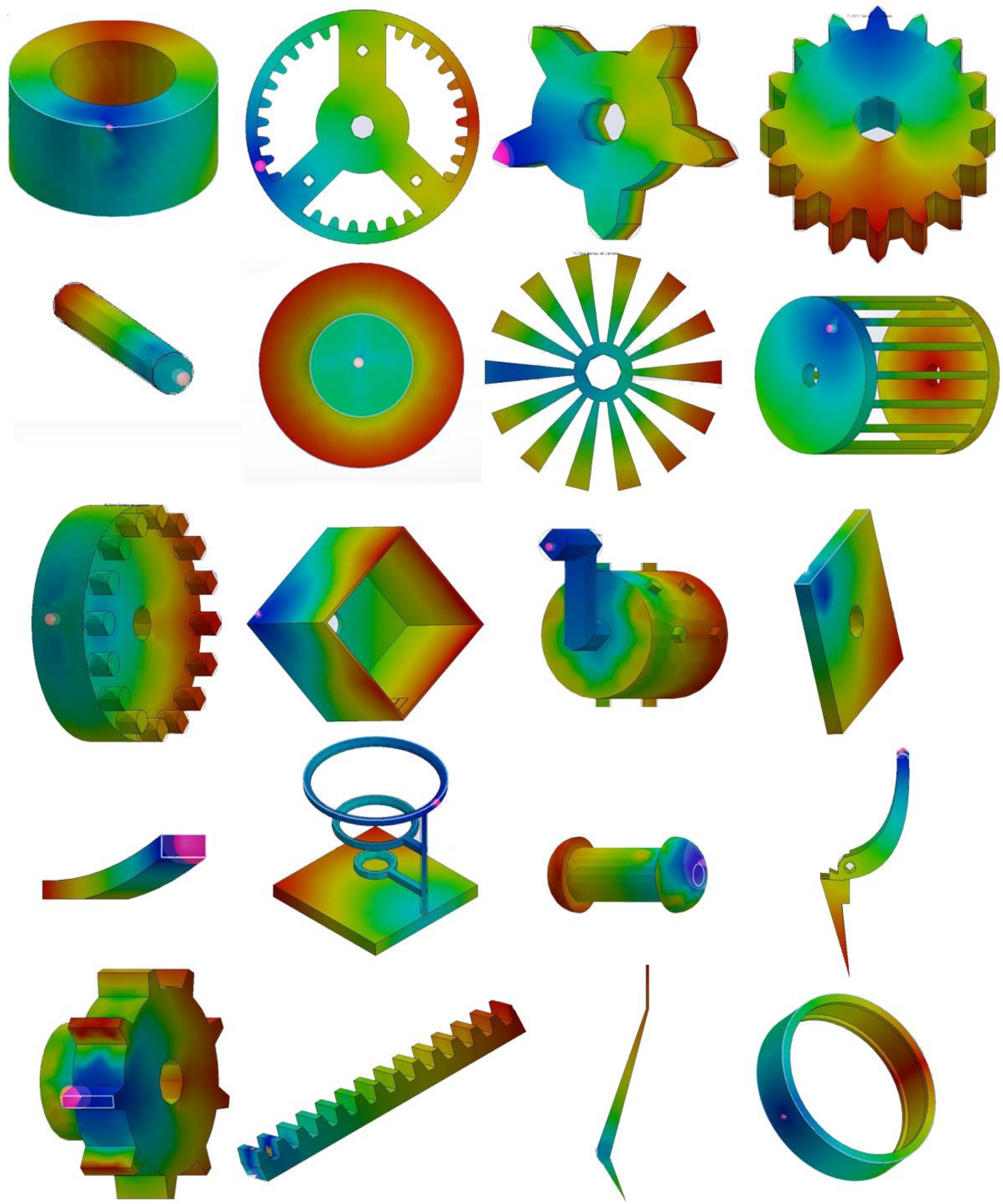
0,01817	0,0554	0,0528	0,0921
0,0623	0,0632	0,034	0,0343
0,0319	0,0201	0,0323	0,0172
0,0552	0,0344	0,0563	0,03
0,055	0,0347	0,0561	0,0302
0,0594	0,0363	0,0603	0,0325
0,0554	0,0341	0,0561	0,0301
0,0554	0,0341	0,0561	0,0301
0,1654	0,0549	0,0466	0,1735
3,9863	0,1911	0,0827	8,321
0,0453	0,0388	0,0462	0,0348
0,1107	0,1145	0,0627	0,0603
0,1946	0,0393	0,0424	0,0996
0,1906	0,191	0,273	0,1739
0,0757	0,2403	0,2042	0,1365
0,3189	0,311	0,1368	0,1719
0,0954	0,2741	0,699	7,163
0,4154	0,2487	0,3251	0,2871
0,1219	0,1157	0,0827	0,0651
0,1855	0,1579	0,068	0,0955
0,0974	0,0978	0,0554	0,0512
0,0342	0,0315	0,0379	0,0259
0,1482	0,0272	0,0282	0,075
0,0825	0,2648	0,2612	0,1357
0,0552	0,1953	0,1832	0,1008
0,1491	0,1484	0,1994	0,1265
0,0825	0,2648	0,2612	0,1357
0,1219	0,1157	0,0827	0,0651
0,1855	0,1579	0,068	0,0955
0,0974	0,0978	0,0554	0,0512
0,0342	0,0315	0,0379	0,0259
0,1482	0,0272	0,0282	0,075
0,0825	0,2648	0,2612	0,1357
0,0552	0,1953	0,1832	0,1008
0,1491	0,1484	0,1994	0,1265
0,0825	0,2648	0,2612	0,1357
0,3021	0,2966	0,0755	0,1531
0,0821	0,1513	0,1508	0,1009
0,3532	0,2202	0,2469	0,2254
0,024	0,1662	0,172	0,1018
0,0142	0,0456	0,0168	0,0256

0,0274	0,0112	0,0118	0,0156
0,0625	0,1235	0,0301	0,0705
0,0912	0,0524	0,0885	0,0484
0,1715	0,0489	0,0445	0,0903
0,0166	0,0916	0,0823	0,0774
0,1012	0,1011	0,1086	0,0575
0,2366	0,2441	0,0796	0,1387
0,1483	0,146	0,0891	0,0834
0,1277	0,2315	0,1993	0,1437
0,3021	0,2966	0,0755	0,1531
0,0821	0,1513	0,1508	0,1009
0,3532	0,2202	0,2469	0,2254
0,024	0,1662	0,172	0,1018
0,0142	0,0456	0,0168	0,0256
0,0274	0,0112	0,0118	0,0156
0,0625	0,1235	0,0301	0,0705
0,0912	0,0524	0,0885	0,0484
0,1715	0,0489	0,0445	0,0903
0,0166	0,0916	0,0823	0,0774
0,1012	0,1011	0,1086	0,0575
0,2366	0,2441	0,0796	0,1387
0,1483	0,146	0,0891	0,0834
0,1277	0,2315	0,1993	0,1437
0,0083	0,0114	0,0053	0,0082
0,0906	0,0333	0,0302	0,0464
0,152	0,0649	0,056	0,079
0,152	0,0649	0,056	0,079
0,162	0,0638	0,0547	0,0837
0,0083	0,0123	0,0074	0,0099
0,0095	0,0142	0,0081	0,0114
0,0082	0,0122	0,0072	0,0096
0,01817	0,0554	0,0528	0,0921
0,0623	0,0632	0,034	0,0343
0,0319	0,0201	0,0323	0,0172
0,0552	0,0344	0,0563	0,03
0,055	0,0347	0,0561	0,0302
0,1219	0,1157	0,0827	0,0651
0,1855	0,1579	0,068	0,0955
0,0974	0,0978	0,0554	0,0512
0,0342	0,0315	0,0379	0,0259
0,1482	0,0272	0,0282	0,075

0,0825	0,2648	0,2612	0,1357
0,0552	0,1953	0,1832	0,1008
0,1491	0,1484	0,1994	0,1265
0,0825	0,2648	0,2612	0,1357
0,3021	0,2966	0,0755	0,1531
0,0821	0,1513	0,1508	0,1009
0,3532	0,2202	0,2469	0,2254
0,024	0,1662	0,172	0,1018
0,0142	0,0456	0,0168	0,0256
0,0274	0,0112	0,0118	0,0156
0,0625	0,1235	0,0301	0,0705
0,0912	0,0524	0,0885	0,0484
0,1715	0,0489	0,0445	0,0903
0,0166	0,0916	0,0823	0,0774
0,1012	0,1011	0,1086	0,0575
0,2366	0,2441	0,0796	0,1387
0,1483	0,146	0,0891	0,0834
0,1277	0,2315	0,1993	0,1437
0,0594	0,0363	0,0603	0,0325
0,0554	0,0341	0,0561	0,0301
0,0554	0,0341	0,0561	0,0301
0,1654	0,0549	0,0466	0,1735
3,9863	0,1911	0,0827	8,321
0,0453	0,0388	0,0462	0,0348
0,1107	0,1145	0,0627	0,0603
0,1946	0,0393	0,0424	0,0996
0,1906	0,191	0,273	0,1739
0,0757	0,2403	0,2042	0,1365
0,3189	0,311	0,1368	0,1719
0,0954	0,2741	0,699	7,163
0,4154	0,2487	0,3251	0,2871
0,4154	0,2487	0,3251	0,2871
0,1219	0,1157	0,0827	0,0651
0,1855	0,1579	0,068	0,0955
0,0974	0,0978	0,0554	0,0512
0,0342	0,0315	0,0379	0,0259
0,1482	0,0272	0,0282	0,075
0,0825	0,2648	0,2612	0,1357
0,0552	0,1953	0,1832	0,1008
0,1491	0,1484	0,1994	0,1265
0,0825	0,2648	0,2612	0,1357

0,3021	0,2966	0,0755	0,1531
0,0821	0,1513	0,1508	0,1009
0,3532	0,2202	0,2469	0,2254
0,024	0,1662	0,172	0,1018
0,0142	0,0456	0,0168	0,0256
0,0274	0,0112	0,0118	0,0156
0,0625	0,1235	0,0301	0,0705
0,0912	0,0524	0,0885	0,0484
0,1715	0,0489	0,0445	0,0903
0,0166	0,0916	0,0823	0,0774
0,1012	0,1011	0,1086	0,0575
0,2366	0,2441	0,0796	0,1387
0,1483	0,146	0,0891	0,0834
0,1277	0,2315	0,1993	0,1437
0,0083	0,0114	0,0053	0,0082
0,0906	0,0333	0,0302	0,0464
0,152	0,0649	0,056	0,079
0,152	0,0649	0,056	0,079
0,162	0,0638	0,0547	0,0837
0,0083	0,0123	0,0074	0,0099
0,0095	0,0142	0,0081	0,0114
0,0082	0,0122	0,0072	0,0096
0,01817	0,0554	0,0528	0,0921
0,0623	0,0632	0,034	0,0343
0,0319	0,0201	0,0323	0,0172
0,0552	0,0344	0,0563	0,03
0,055	0,0347	0,0561	0,0302
0,0594	0,0363	0,0603	0,0325
0,0554	0,0341	0,0561	0,0301
0,0554	0,0341	0,0561	0,0301
0,1654	0,0549	0,0466	0,1735
3,9863	0,1911	0,0827	8,321
0,0453	0,0388	0,0462	0,0348
0,1107	0,1145	0,0627	0,0603
0,1946	0,0393	0,0424	0,0996
0,1906	0,191	0,273	0,1739
0,0757	0,2403	0,2042	0,1365
0,3189	0,311	0,1368	0,1719
0,0954	0,2741	0,699	7,163
0,4154	0,2487	0,3251	0,2871

Micro injection processes of plastic parts (CAE systems).



Annex 2. Tests carried out with the designed system.

System test, defect analysis and cycle counter (material ABS).

Ci. No	Press. Inject	Material Temperature	Mold Temperature	Filling time	Vol.	Vacu.	Burns	Incomplete parts	Flas	Sink marks
1	111	219	32.1	13	15.3	2		2		
2	111	225	35	23	15	3				1
3	111	230	32	20	18	2				1
4	115	235	30	18	12		2		5	
5	111	230	30	17	10					
1	100.3	218.55	32.26	1.38	35.26	2	2	4		
2	105	218	32	10	35	2	1	3		1
3	111	215	30	15	32	1	1	1		
4	111	210	30	17	32.5					
1	99	220	32	0.96	35.74		2	4		3
2	99	215	32	4.7	25.4		1	2		2
3	98	210	32	10	19					1
4	98	210	30	10	17					
1	90	146	48	7.68	35.4	2			3	3
2	93	130	40	6		1	2		2	2
3	93	180	35	5		1			1	2
4	91	220	30	3		1				1
5	90	239	30	3	35.2					
1	110	220	32	1.88	35.9		1	2		2
2	115	218	30	2.5	35			1		1
3	118	218	30	3	35					
1	99.9	238	32	2.65	35.46		1	2		1
2	95	236	33	8	36	1	1		2	1
3	90	230	35	6	35	1		1		
4	90	230	34.9	6	35					
1	100	220	32	2.38	35.24			2		3
2	100	230	32	2.5	35	1				

3	90	245	30	3	35.5		1		2	
4	90	240	30	3.2	35.5		1			
5	90	239	30	3	35.2					
1	90	220	35	0.9	33	1	2	5		2
2	85	215	32	10	32			2		2
3	70	205	35	19	31				2	1
4	50	210	31	15	36			1		
5	57	210	30	16	35	1				
6	60	210	30	16	35					
1	80	225	32	2	32	2		1		4
2	70	230	35	3	35	1			2	
3	65	235	35	3	35		1			
4	67.5	240	35	3	35					
1	90	210	30	3	35	1		5		
2	90	220	32	10	35			3		1
3	100	225	35	15	36			2		1
4	90	230	35	20	36				1	
5	90	230	36	19	36					
1	70	210	30	5	30	2		4		1
2	68	220	30	10	30	2		2		1
3	65	225	31	12	32	1		1		
4	60	230	32	14	35		1			
5	61	230	32	14	35					
1	80	220	32	5	30	3			3	
2	75	225	30	4	32	2			2	1
3	69	230	30	3	30	1				
4	59	230	30	3	30					
1	92	220	35	4	32			1		1
2	90	228	30	6	35					1
3	90	230	30	6	35					
1	100	220	30	2	32		2		2	
2	95	215	30	5	33		1			1
3	90	210	31	3	35	1			1	
4	90	210	32	4	35					
1	80	200	30	4	30	2		2		1
2	82	215	31	6	32	1		1		1
3	85	218	30	7	33	1				
4	90	220	30	7	35					

System test, defect analysis and cycle counter (material PP).

Ci. No	Press. Inject	Material Temperature	Mold Temperature	Filling time	Vol.	Vacu.	Burns	Incomplete parts	Flas	Sink marks
1	100	205	32	13	32	2		1		3
2	105	220	31	15	15	1			2	
3	110	230	30	15	12		2			
4	111	225	30	15	12					
1	112	205	34	10	35			1		1
2	110	205	35	12	35					
1	90	200	30	5	7	4		4		
2	94	210	35	10	15			2		
3	95	215	35	12	15					
1	90	220	35	10	32		3		1	4
2	85	215	32	8	31		2		2	
3	81	210	30	8	31					
1	89	215	35	7	35	1			2	2
2	92	230	33	4	30	1		1		
3	96	230	31	5	32	1				
4	95	230	30	5	32					
1	99	205	32	10	35	1			1	2
2	105	210	33	9	30				1	
3	110	210	34	8	30					
1	99	220	30	10	30		1		1	
2	95	220	31	10	30					
1	110	230	30	6	32	1		2	2	
2	77	210	32	13	32	1			1	
3	75	215	32	12	30					
1	90	220	30	5	35			2		4
2	80	225	30	8	37	1			1	3
3	72	230	31	7	40					2
4	69	230	31	7	39					
1	95	210	32	10	30	1		1		
2	96	210	32	15	30					
1	90	220	35	10	32		3		1	4
2	85	215	32	8	31		2		2	
3	81	210	30	8	31					
1	75	215	32	10	35		2		2	3
2	70	210	32	8	40					1
3	69	210	32	7	39					

1	90	215	30	12	30		2		2	2
2	92	210	30	8	30	1	1			
3	94	210	32	10	31					1
4	94	210	31	10	31					
1	100	215	30	10	30	1			1	
2	99	220	30	7	30					
1	90	200	35	10	30	2				2
2	95	205	33	10	30				1	1
3	94	210	33	10	31					