Quality Control and Parameter Optimization of Injection Molding Product: A Comprehensive Review

Amit Bhalchandra Panchal[1] Jalpesh H Solanki[2] Divyesh B. Patel[3]

[1]Department of Production Engineering, Lukhdhirji Engineering College, Morbi, Gujarat, India.

[2,3]Department of Mechanical Engineering, Lukhdhirji Engineering College, Morbi, Gujarat, India.

***Corresponding Author :** Amit Bhalchandra Panchal
*Email:-abpbits@gmail.com

Abstract - For many years, injection molding is adopted as the most suitable manufacturing process in the production of complex plastic components. It is very difficult to boost the product's quality stability to attain a higher forming speed and higher automation in the injection moulding process because the process often disrupted by numerous inevitable deviations. The settings for different process parameters and machine parameters have quite a major influence on the overall product quality and its performance of the injection moulding process, which shows the final product quality as output responses. Identifying the perfect process parameter settings so that numerous responses may be optimized at almost the same time is becoming a significant research challenge these days. Smart manufacturing is at the heart of the new industrial revolution, and it will continue to be the primary means of transforming and upgrading the manufacturing industry in the upcoming decades. Melt temperature, the temperature of mould, injection pressure, and velocity of molten polymer while injection, injection time, pressure of molten polymer while holding into the mold cavity, holding time of molten polymer, and cooling time are the variety of input process parameters. While mechanical characteristics, flaws such as warpage, volumetric or dimensional shrinkage, sink mark on outer surface, residual stress, and surface finish/roughness are examples of responses. To study and optimize the molding process, researchers have used a wide range of methods. Mathematical modeling, simulation, design of experiments, Taguchi methodology, analysis of variance - ANOVA, response surface methodology - RSM, evolutionary algorithm (EA), artificial neural networks - ANN, genetic algorithms - GA, fuzzy logic, particle swarm optimization - PSO, are examples of these techniques. This paper presents a review of the numerous strategies that used till date for optimizing the key injection moulding parameters, as well as their benefits and challenges. In the review, it is discovered that a perfect injection molding process, which takes care of overall quality control is still being researched upon. The process parameters involved in injection molding, required response, and the methodologies used for optimization of overall injection molding process are discussed throughout this paper.

Keywords - Injection molding (IM), process parameter, optimization, warpage, shrinkage

1. Introduction

The injection molding (IM) process, is among the most frequently employed plastic fabrication processes for large-scale plastic product manufacturing [1]. A large number of reliable and variety of products, dimensionally accurate products, can be produced in bulk makes the injection molding process more and more suitable plastic processing process. There are also some other advantages to this technique, like as the light weight of the parts and the excellent surface polish of optional components, which make it preferable to other procedures. It involves temporary fixing two halves of the mold together into which cavity is previously formed and pressurized molten polymer is deposited into the mold cavity. Molten polymer with high pressure ensures the rapid filling and also ensures the mold is fully filled. The cavity of a mould is kept to a consistent pressure for the packing stage once the filling phase is nearly complete. After that, the mold is allowed to cool for a specific time period. To finish filling the remaining vacant space in the mold cavity and try to compensate for the shrinking, packing pressure is applied and then it is opened and the part is finally ejected from the mold. Injection moulding is a process that involves the injection of molten material into a mould, several process parameters must be supplied while doing so. The value of this process parameters is determined by a variety of factors, including the type of plastic, the size of the component to be produced, dimensional tolerances, and so on. These variables have an impact on the final product's quality and must be carefully chosen. For the following reasons, this job remains difficult. (a) There are usually a lot of variables that influence product quality. (b) These parameters have nonlinear and time-varying impact and they collaborate with one another. (c) Traditional methods of parameter optimization, such as trial - and - error, rely heavily on individual expertise and are not any longer capable of meeting demands. As a result, finding a way to optimize these process parameters based on scientific data analysis is both a fascinating research topic and a valuable application. While there are numerous key processing parameters concerning the quality of product.

These include parameters like injection pressure, the speed of molten polymer while injection, injection time, melting temperature, the temperature of mold, packing pressure, packing and cooling time [2-5]. The findings of various researchers are inconsistent when it comes to the most important process factors. This is owing to the wide range of variables connected with injection moulding, such as mould size, machine size, material variations, and product form variation. As a result, the product's quality is thus naturally difficult to predict or if predicted, it is difficult to control without using the advanced computer simulation or optimization. Postawa and Koszkul [6] suggest that shrinkage results in the final product and the weight of injection-molded component is a function of processing conditions only.

In today's industrial practice, in determining the best suitable injection molding process parameters, people use reference books or handbooks and adjustments of various parameters through trial and error by experienced engineers [7]. Many studies have focused on traditional process parameter optimization, which is based on trial-and-error and experience. It is no longer sufficient to employ such trial - and - error method to determine injection moulding process parameters in the current era of global innovativeness in the injection moulding industry. To search for the right process parameter In order to obtain high quality goods efficiently and affordably, parameter setup is acknowledged as the most practical way and critical phase in plastic injection moulding. In a majority of the earlier research attempts, as a quality indicator, warpage and shrinking have been utilized and the objective is to achieve the most effective combination of processing parameters for reducing warpage and volumetric shrinkage as much as possible.

To improve the operation parameters of an Injection Molding method and make products of the highest standards of excellence, a variety of optimization research methodologies have been used. However, there remains a difficulty for field researchers in terms of practical implementation due to a variety of causes of variation during the molding process. It tends to results in failures and, as a result, resource wasted. Overall process monitoring and control, improvement of operational parameters, the mould design in accordance to the detailed specifications of the part, and the design of cooling channel based on the characteristics of the mould cavity would all be benefited by the use of AI technologies. To have a good product quality for the Injection Molding process (IM), soft computing techniques such as differential evolution, genetic algorithm, and particle swarm optimization techniques are proposed in various literature. These methods were used in order to acquire necessary control over the process and the quality of product during the process. Although operation circumstances really had the greatest impact on the quality of molded plastic parts, determine the best set of process parameters has become critical to improving component quality. The injection molding method simply divides into some important steps, those are heating of appropriate plastic material, injection of molten polymer into mold cavity, packing, and lastly cooling. Therefore, few processing parameters, like the melting temperature, the temperature of mold, the time for injection, injection speed, injection pressure, packing time, packing pressure, cooling temperature and cooling time, all majorly affects adversely on the quality of the final molded product. Now, this optimal processing parameter adjustment normally varies as the wearing of machine components, requirement of the materials whiles the production process. In such circumstances, the derived setting of operational process parameters can produce the faulty items and ultimately reduce product quality and production efficiency as well. Until now, the whole injection moulding process has been manually monitored, and operational process parameters have been modified by qualified engineers in the industry. These practice results in various losses like the loss of time which required to control the production process, loss of material being wasted due to improper adjustment of influenced process parameter, and finally financial loss associated with manpower utilization. Defining process parameters that are well-defined required to improve the mentioned situation to achieve excellence in quality control of the injection molding process (IM). Analysis of variance - ANOVA is commonly used to uncover the most significant process parameters [8, 9], neural networks [10-12] and genetic algorithms. Researchers have extensively employed the artificial neural network (ANN) technology for a wide range of applications in a variety of fields due to its advantages over traditional polynomial and linear regression methods for optimization due to its non-linear analysis capabilities [13, 14].

As already established, multiple factors controlling injection moulding must be thoroughly examined before determining the possibilities of making a parts of the needed quality characteristics. These factors can be categorized into three categories [15]:

1. Machine parameters including the parameters like, the temperature of the coolant used, pressure for packing the material and pressure to hold the molten polymer, injection pressure, injection speed, screw speed, and so on are considered as independent variables.
2. Process parameters including the parameters like, mold and melt temperature, cooling temperature, melting pressure, shear stress developed in the molded product, injection time and the time of filling the molten polymer, the time for packing, holding and cooling the molten polymer, injection rate, polymer flow rate, and so on are considered.

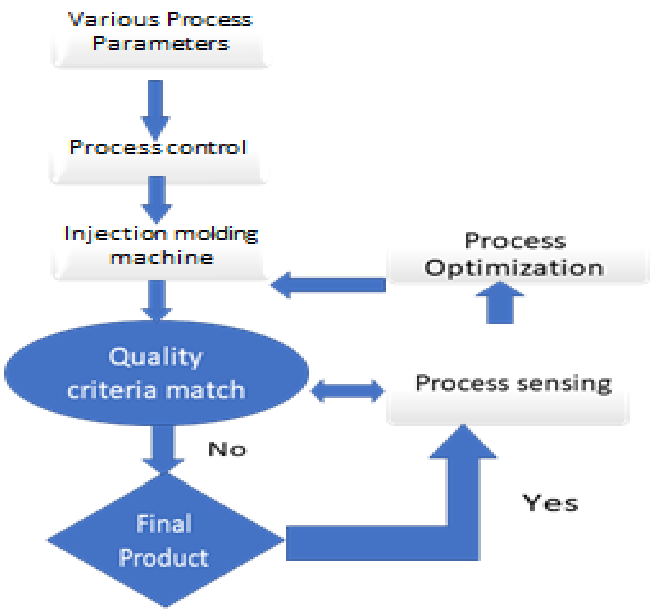

FIGURE 1: The smart injection molding process

The advanced sensors control the machine parameters, or the parameters can be controlled by advancing various machine components. The combination of factors, process conditions as well as material characteristics generally affects these process parameters. The final responses, on the other hand, are the objective variables that must be carefully managed in order to achieve the needed complicated shape and dimensional precision, as well as surface finish. However, difficulties occur in identifying the significant input parameters with output responses. Experimenting with the output responses associated with the various possible combination of parameters is still a difficult task. Hence, there has been a requirement of an optimization process that can design the experiments with a significant number of trial runs, the determination of significant process variables that affect the molding process, and the precise prediction of final outcomes. This research explores historical and present research that has been using various optimization approaches to enhance the different parameter setting in order to attain the desired quality in an injection molded product. The present paper is framed in the following way: section-1 introduces the concept of injection moulding optimization, followed by section - 2 on prior research employing various optimization strategies, and finally section - 3 shows the conclusion of the paper with a few research gaps which can be considered as future directions in this area.

2. PAST APPROACHES FOR THE PARAMETER SETTING

Trial - and - error strategies generally depends on the expertise of the engineers and technicians were adopted in the beginning phases of injection moulding to achieve acceptable products with few flaws. In the last few decades, many methods for forecasting the possible combinations of input parameters or the process have been presented. [16]. Case-based reasoning technique, process-window method, and expert system based system are three types of approaches.
The correlation between melt temperature and injection pressure is explored in the process window method. The frontiers of the process window are set based on following two circumstances: (I) too high injection pressure causes flash, and a low pressure yields a short shot, and (II) very high melting temperature destroys polymer material, whilst a lower melt temperature necessitates large injection forces. Various process parameters were optimized using these optimization methods [17-23]. Here, this approach is unable to handle multiple inputs and multiple output (MIMO) in the injection process.

Non-iterative methods generally depend upon experimental results. They are able to provide initial operating process set up or give path to optimization and they are very simple to execute as it requires very little computation. The methods has been extensively used in research and innovation activities, includes the following methods: case-based reasoning technique (CBR) [1, 18, 24, 25] for the estimation of the cost for injection molds and various molding parts, for adjustment of various molding parameters, the method may be utilized to adjust the starting parameters and optimize them online, considerably reducing the moulding trial experiments and reliance on human specialists, [26, 27] expert system, fuzzy system [28]. The expert system method is a sub-category of artificial intelligence (AI) techniques. But to achieve accurate solutions, a tremendous amount of knowledge from various domains is required to establish expert manufacturing systems.

3. Taguchi method for the design of experiments (DOE)

The typical scientific experimental design methodologies are very robust and not frequently utilized for optimization purpose. A vast number of experiments runs have to be carried out when the number of process parameters are increases. Tang [29] established the Taguchi methodology to increase product quality in injection molding process. It is capable of effectively resolving product quality issues. Taguchi parameter design approach, might only choose one of the best possible combination of provided processing parameter levels that comprise some discrete values. The Taguchi method is among the most common non-iterative optimization techniques. The Taguchi method assists us to better comprehend the characteristics of the process and it also investigate the impact of these input parameters on the responses of the process. It also provides an optimization setup based on the results of experiments and relevant information collected. It follows into the determining the combination of the experimental processing parameters with their best possible levels, designing of experiments and then carry out experiments and finally the data analysis. The impact of all processing parameters on the end product quality can be determined by examining the quality of injection molded items with various parameters through analysis of variance - ANOVA, range analysis, and signal-to-noise ratio (S/N) analysis. It has been used in design and analysis of optimizing the parameters in manufacturing [30]. The Taguchi methodology is used in design of experiments (DOE) with the aim of achieving desired output by selecting the most appropriate combinations of operating parameters with less time, the minimum budget, and the minimum number of experimental trials [31, 32]. For solving a complex engineering cases, the Taguchi methodology explains a design of orthogonal arrays-OA which has a very few number of experimental runs. Moreover the findings of the experiment are again modified into a signal-to-noise (S/N) ratio. The S/N ratio is a way of comparing how far quality characteristics deviate from the required response values. In the analysis of the S/N ratio, there are generally three kinds of quality characteristics: (1) the lower is better, (2) the higher is better, and (3) the nominal is better. Based on this S/N analysis, the S/N ratio of each level of process parameter is calculated. [30]. Finally, reasonably ideal parameter settings can be established. Analysis of variance - ANOVA and range analysis is also used for identification of the influence of the processing parameters. It uses orthogonal arrays to identify optimal parameter combinations according to the signal-to-noise (S/N) ratio, taking into account the number of processing parameters along with their levels, as well as the total number of experimental trials to be completed. Taguchi L273 13 denotes a problem with 13 process parameters, each with three levels, necessitating just 27 experimental runs instead of 313 to achieve the required outcome. Huang [33] used the Taguchi approach to determine the impact of the parameters on the product's micro-features.

Chang and Faison [34] applied the Taguchi methodology to establish the best optimum set of input process parameters to reduce component shrinkage and then used analysis of variance -ANOVA analysis to determine the corresponding contribution of each individual input parameter and finding out the most key parameters majorly affecting shrinkage in injection moulding. Other efforts, such as minimization of warpage and volumetric shrinkage using signal-to-noise (S/N) and the analysis of variance -ANOVA analysis and found that warpage and shrinkage are reduced by 2.17 percent and 0.7 percent, respectively [35], and reducing of shrinkage in polypropylene (PP) and polystyrene parts, have used similar approaches in injection moulding [36]. The Taguchi method is applied to adjust the process parameters in injection molded vehicle plastic bumpers made from polycarbonate to avoid silver streak defect [37]. The experimental results shows that the packing pressure has the biggest impact on the warpage, and it is followed by mould temperature, melt temperature, and packing time [38]. The Taguchi method is used to determine the factors that influence shrinkage and warpage in thin-wall cell phones covers [39]. The effect of design parameters on volumetric shrinkage was investigated in the experiment [40]. The melt temperature appears to be the most effective factor in causing warpage of a rectangular plate, based on the findings of experiment it was found that melt temperature at 240 °C, filling time of 0.5 sec, packing pressure is 90 percent, and packing duration is 0.6 sec are the best factors for reducing warpage [29]. In order to increase the compressive property of a brake booster valve body, Wang [9] adjusted input parameters, while Karasu [41] minimized the number of experimental runs required for mass manufacturing. Using the Taguchi technique as a guideline, [42, 43] the experimenter examined the influence of process parameters on the correctness of lens geometry. The melting temperature plays a vital impact in the shrinkage reduction on the molded item, according to the final observation using the signal-to-noise S/N ratio [44]. Wang [9] investigate the requirement of number of gates, the size of the gate, polymer temperature, mold temperature, filling volume conversion, V/P switch over, and cooling time with analysis of the signal - to - noise ratio (S/N) and analysis of variance -ANOVA and found that 12% increased in compression strength compared to the average compression strength of the overall experiment. The melt temperature of a specific material and the mould temperature are two parameters that have a considerable impact on the strength of the material [45]. Taguchi optimization and the ANOVA approach were shown to be very beneficial in discovering the most critical moulding process characteristics that affect volumetric shrinkage and optimizing controlling parameters to get minimal shrinkage in molded parts, according to Ramkumar [46]. Along with there are other different design of experimental methods available such as central composite design - CCD, box behnken design -BBD, and latin hypercube design - LHD. Melting temperature, packing pressure, and packing time are the processing factors that have the greatest impact on gear shrinkage, according to the Taguchi optimization approach [47]. Table - 1 shows the most common design of experiment methods used in literature.

TABLE 1. Summary of the DOE method used for the optimization method

Various DOE methods used	Response
CCD - Central composite design	Tensile strength [48] Shrinkage and warpage [49-51] Sink marks [51, 52]
BBD - Box–Behnken design	Cycle time and Warpage [53-55]
LHD - Latin hypercube design	Shrinkage [56] clamping force [56] Warpage [10]
OED - Orthogonal experimental design	Warpage [30, 57, 58] Shrinkage [57, 59] Mechanical properties [9] Residual stress [53]

Certain limitations are also associated with the Taguchi approach. It entails determining the optimum level of a process parameter from a predetermined set of levels. Second, selecting process parameters, as well as their ranges along with their levels, necessitates a comprehensive understanding of the entire injection molding technique. Non-iterative optimization methods are simple to apply and they have a long history in industry. The Taguchi approach, on the other hand, can only create discrete parameter combinations and cannot solve multi-response problems. As a result, obtaining the global optimum process parameters is difficult. Due to the difficulties of acquiring knowledge, establishing a knowledge base for an expert injection molding system is also a challenge.

Advanced computational methods

As application of Injection moulding (IM) has progressed during recent years, it requires advanced sophisticated computational techniques. Hard computing, which uses finite element or finite difference methods, and soft computing, which uses AI approaches to analyze the process environment and anticipate injection moulding performance, are two advanced computational methodologies.

Hard computing techniques

In Injection moulding, hard computing is done with commercial software packages or optimization modules.

Nowadays, numerous advanced software is available by which simulation, analysis, and data interpretation can be done. Moldflow is one example of a software package that has been used in a number of studies to identify significant parameters affecting majorly on the shrinkage of injection molded components [60]. Moldflow was used in combination with the Taguchi approach to obtain the optimal process parameters in gas-assisted moulding components by minimizing warpage [61]. Moldflow is used in conjunction with the Taguchi methodology to investigate the impact of process parameters on ultra-thin wall polymer component moulding. The findings of the experiment reveal that part thickness is the most important parameter in moulding, that metering size and injection rate are the most important factors in the moulding process, and that increasing the injection rate can significantly enhance the filling ratio [62]. In the case of optimization, Kriging models used to optimize the warpage in plastic cell phones to minimize computational resources than it is required by Moldflow analysis [63-65], to reduce warpage and shrinkage, use a sequential simplex approach paired with Moldflow [5], etc.

Hard computing involves finite element analysis (FEA) which requires very huge computational time and high expense, which may not be available on the shop floor, a method using simulation analysis is majorly used for research purposes to characterize the impact of these machine parameters and process parameters on the final product quality. ANSYS, Moldflow, Moldex3D, and HsCAE are the most common software packages to simulate this process. But this software is also unable to consider machine capabilities while simulation.

Soft computing techniques

Artificial intelligence (AI) approaches are rapidly being used to increase the efficiency and productivity of the injection moulding process. The optimization of intelligent parameters is a key aspect of intelligent injection moulding. Unsuitable settings can result in product failures. Artificial neural networks, evolutionary algorithms, and hybrid methodologies are examples of frequently used artificial intelligence in injection moulding soft computing.

Artificial neural network (ANN)

An artificial neural network (ANN) is a deterministic model which is used to processes information through millions of inter- linked neurons that react to each input using weights, thresholds, and transfer functions that may be changed. The key benefit of employing ANN for injection moulding process parameter optimization is its potential to map out non-linear correlations between a range of input and output data. Injection time and injection pressure of the metal moulding process that used a feed-forward neural network combined with the Gauss training approach have been reported in a number of works using ANN in injection moulding [66]. In order to get the appropriate final response in terms of dimensional precision, modifications in process parameters are required [67]. With using neural networks, Kenig [68] were able to regulate and anticipate mechanical characteristics such as tensile modulus in the injection moulding process pretty precisely and in an acceptable amount of time. Kurtaran [69] used the response surface technique (RSM) and the artificial neural network (ANN) to reduce warpage in thin-shell plastic components. The neural network model is developed using a forward mapping ANN model in which all processing parameters considered as input parameters and by using reverse mapping ANN model in which response are considered. Through this experiment, it was found that molding and melting temperature along with injection velocity and packing pressure are responsible for dimensional shrinkage [70]. The Artificial Neural Network is used to determine the best injection molding processing parameters that permit for the least amount of flaws in the injection-molded object [71]. The Artificial Neural Network method and Moldflow analysis are used to establish the relation between the processing parameters on the volumetric shrinkage of the component made from PP material. The experimental results shows that ANN model is able to establish the relation between the processing parameters on the volumetric shrinkage with good accuracy. It was also found that the amount of material pressed into the mould has the greatest impact on shrinkage, followed by the crystalline structure and orientation of the material. [72]. Shi [73] used an ANN model to optimize process settings to reduce injection moulding component warpage. Due to their quick response and great accuracy, the back propagation neural networks (BPNN) and radial basis function network (RBFN) are also widely preferred for optimizing injection molding method [74, 75]. BPNN is supported with experimental data utilizing computer-aided engineering (CAE) software, which reduces the time required for planning and tuning injection moulding process parameters [13]. By developing correlations between process parameters and warpage of injection-molded vehicle glove compartment cap, BPNN was trained and evaluated with data supplied by Moldflow software and FEM simulation for determining an ideal set of process parameters to minimize warpage. It has been established that the system can accurately anticipate the warpage of plastic component within a 2% error margin. The warpage value can be narrowed by approximately 33%. The experiment also reports significant fall in cooling time. [76]. To assist engineers in identifying optimal process conditions, Xu [77] combined a back-propagation neural network method - BPNN with particle swarm optimization method (PSO) to minimize defects in injection molded parts, etc.

But how ANN works, the output response is completely uncontrollable by the user after adding input data and describing a architectural style in general for the injection molding process. Furthermore, determining the optimal number of nodes and hidden layers is a time-consuming effort that necessitates rechecking the algorithm whenever any data falls outside of the expected range. BPNN models may take longer as the non-linearity of test data rises.

Evolutionary algorithm (EA)

Due to their capacity to find global optima even without numerous response targets, evolutionary algorithms have become increasingly significant in optimizing injection moulding process parameters in recent years. Genetic algorithms (GA) for optimizing processing parameters are used in injection moulding process optimization employing EAs [39, 78, 79] and for minimizing the effect of shrinkage in runner diameters of molded part [80], multi-objective genetic algorithm (GA) for determining the size of the runner in multiple cavity injection molds [81], multi-objective genetic algorithm for studying the features of performance of injection molding (IM) machine [82]. Genetic Algorithm (GA) used to improve input process parameters to achieve the required result in form of dimensional shrinkage in injection-molded plastic part. It was also found that the overall dimension shrinkage error is nearly 7% between the anticipated value and experimental measurement. The shrinkage in the transverse and longitudinal directions are clearly improved by 85 percent and 63 percent, respectively [83]. With the premise that the majority of injection-molded specimens have a sheet-like form, particle swarm optimization (PSO) is used to estimate process parameters. [84]. The multi-objective optimization problem was solved using NSGA-II to identify factors in the machining process that have a substantial impact on component quality, productivity, and cost. The results suggest that the proposed method can be used to optimize machining while managing conflicting objectives [85]. Bouacha [86] compared the performance of the non-dominated sorting genetic algorithm (NSGA-II) and the particle swarm optimization-based neural network. The NSGA-II methodology was proven to perform better than the PSO-NN methodology. Table 2 shows the most common evolutionary methods used for the optimization of the injection molding process parameters in literature. Evolutionary algorithms (EA) also have certain limitations, includes their dependency on the selection of fitness functions, the range process parameter.

Hybrid approaches

It is preferable to combine two or more strategies in order to benefit from their unique advantages, which would not have been available if they were used independently. Hybrid approaches, such as GA combined with the Taguchi method, are used to reduce molded component warpage. [104], GA in collaboration with ANN can also be used to optimize the initial process parameter values. [105]. The experimenter suggest to combine GA with BPNN to attain the best quality in terms of shear stress [106] and to reduce volumetric shrinkage [13]. This experiment shows that to modify the runner sizes to balance the flow through NSGA. The objective of the study is to improve the part quality by reducing the warpage [81], The taguchi method combined with genetic algorithm (GA) and BPNN to identify the set of data in multiple-input single-output (MISO) by optimizing molded product weight [107].

To improve the processing parameters, the suggested approach combines Taguchi's parameter design method, back-propagation neural networks, evolutionary algorithms, and engineering optimization ideas [108]. For determining mechanical qualities by calculating an ideal combination process parameters, the Taguchi technique and response surface methodology (RSM) can be integrated with BPNN and GA [104]. Moldflow analysis and orthogonal array experimental methods, together with BPNN and genetic algorithm (GA), can be apply to find the best set of processing parameters for reducing warpage and clamping force [109]. A hybrid method can be effectively used including back-propagation neural network (BPNN), genetic algorithm (GA), and response surface methodology (RSM) to identify an optimal processing parameter setting of the injection molding process. The experiment proves that the applied hybrid optimization method is very effective for optimization of injection molding processing parameter [110]. Using the dia. and length of the runner system as controlling parameters, the simulated annealing (SA) method was employed to find the best process parameter for achieving lowest warpage in molded parts [111]. This method combines a back propagation (BP) neural network method with a global intelligence optimization algorithm, such as a genetic algorithm (GA) to optimize the parameters as per specifications required. By considering various parameters, clamping force and warpage was optimized [4]. The Latin hypercube sampling approach was integrated with the Kriging method and multi-objective PSO (MOPSO) to create a superior Pareto frontier by lowering simulation cost. It was clear from the experiment that multi-objective optimization method can help us to achieve higher computational accuracy and efficiency for few sample size [112]. The experiment employ the ANN and an artificial bee colony (ABC) approach to select the best set of process parameters by minimizing warpage of molded components [113]. The Taguchi technique and ANOVA combined with GA and PSO were used to get optimal input and output process parameters [89]. Short shot as a design constraint and process parameters as design variables, Moldex3D software and the radial basis function (RBF) network based sequential optimization approach were used to minimise warpage in the plastic molded components [11]. Table 3 shows the most common hybrid approaches used for the optimization of the injection molding process parameters in literature.

TABLE 2: Summary of Evolutionary methods used for the optimization method

Various Evolutionary methods used	Response
GA - Genetic algorithm	Warpage [69, 87-90] Shrinkage [88, 91, 92] The cooling process [93] Sink mark [52] Short shot [94] Velocity control [95]
PSO - Particle swarm optimization	Cycle time [10] Mechanical properties [12] Warpage [89, 96, 97] Torque and speed [98] Shrinkage [99, 100]
Non-dominated sorting genetic algorithm II (NSGA-II)	Quality characteristics [101] Mechanical properties [102] Energy consumption [101, 103] Warpage [3, 91] Shrinkage [3, 91] Residual stress [91] Sink mark [3]

TABLE 3 Summary of hybrid approaches used for the optimization method

Various Hybrid methods used	Response
ANN - Artificial neural network	Cycle time [28, 87] Clamping force [53]

	Mechanical properties [11, 12, 54] Energy Consumption [114] Warpage [73, 115] Shrinkage [100]
Kriging model	Warpage [116-119]
SVM - Support vector machines	Cycle time [10, 56, 87] Product weight [120]

Real-time techniques

The present requirement is to develop a process that has the ability to be customized to meet the needs of users and to include changes in the process as a result of real-time optimization throughout the injection moulding process. The formulation is a new real-time method that not only determines the input parameters accurately but also enhances the process performance during the moulding process.

Li [72] suggested a genetic algorithm (GA) based real-time process parameter optimization system that takes into account the original injection moulding process parameter set up and allows for online identification of defect and repairing. Only three quality indices are considered in the optimization model, and their values are estimated using approximate approaches that may not be correct in some circumstances.

Zhao [121] designed an algorithm that collects inputs from the injection moulding machine's sensors and continually monitors the operation in real time, differentiating between phases. In the experiment, the filling-to-packing time and switch-over point, as well as the packing time, are optimized depending on the information collected by the procedure.

4. CONCLUSION

This review paper introduces various optimization methods for injection molding and shows recent studies in this area. In the context of parameter optimization, There are numerous defects occurred in a injection molded component, but the most common ones are warpage, shrinkage, and formation weld line on components, and studies found in the literature are concentrated on reducing these defects as much as possible. Intelligent algorithms in association with surrogate models are a commonly used optimization technique and have proven excellent outcomes. According to the findings from the literature review, there is still need for further research on the topic of injection moulding process parameter optimization. In the plastic injection moulding (PIM) process, there is a lot of room for quantitative modeling and optimization. There are numerous techniques/tools that may be used to investigate and analyze the molding process. Here are a few suggestions.

1. Components like Plates, Pipes, lances have been explored many times but no formal research efforts have been reported for parts like Plastic gears or bottle caps which have complex geometries, and are also difficult to maintain dimensional accuracy in mass production. If such kind of advanced computational methods is applied to these intricate geometries, the reliability and repeatability of techniques can be verified.
2. A combination of feedback control along with machine learning may be helpful to get overall control over the product quality.
3. Online tracking of various responses is still difficult, and a feedback system is required to be established which can improve the parameter range.
4. To move towards sustainable, green manufacturing, IoT technologies should be adopted.

Today's industrial scenario demands quick solutions to manufacturing problems. Complex design considerations, close tolerance requirements in a very short period definitely require for a proper optimization method which provides an accurate prediction of parameters associated with the injection molding process. This research conducts a review of several strategies utilized so far in the optimization of plastic injection moulding parameters for the optimum quality. It is detailed how trial and error procedures are used to obtain high-quality goods based on the experiences of engineers and operators. Moving towards the accurate prediction of different input and output parameters has been gradually improved with development in various optimization techniques. There are also significant downsides in various procedures that are described. Finally, new directions in the field of injection moulding process optimization are proposed.

References

[1] Han, S.-Y., et al., A new process of gas-assisted injection molding for faster cooling. Journal of materials processing technology, 2004. 155: p. 1201-1206.
[2] Dang, X.-P., General frameworks for optimization of plastic injection molding process parameters.

Simulation Modelling Practice and Theory, 2014. 41: p. 15-27.
[3] Zhao, J., et al., Multi-objective optimization design of injection molding process parameters based on the improved efficient global optimization algorithm and non-dominated sorting-based genetic algorithm. The International Journal of Advanced Manufacturing Technology, 2015. 78(9-12): p. 1813-1826.
[4] Yin, F., H. Mao, and L. Hua, A hybrid of back propagation neural network and genetic algorithm for optimization of injection molding process parameters. Materials & Design, 2011. 32(6): p. 3457-3464.
[5] Farshi, B., S. Gheshmi, and E. Miandoabchi, Optimization of injection molding process parameters using sequential simplex algorithm. Materials & Design, 2011. 32(1): p. 414-423.
[6] Postawa, P. and J. Koszkul, Change in injection moulded parts shrinkage and weight as a function of processing conditions. Journal of materials processing technology, 2005. 162: p. 109-115.
[7] Choi, G., et al., Optimization of process parameters of injection molding with neural network application in a process simulation environment. CIRP annals, 1994. 43(1): p. 449-452.
[8] Sánchez-Sánchez, X., A. Elias-Zuñiga, and M. Hernández-Avila, Processing of ultra-high molecular weight polyethylene/graphite composites by ultrasonic injection moulding: Taguchi optimization. Ultrasonics sonochemistry, 2018. 44: p. 350-358.
[9] Wang, Y.-q., J.-g. Kim, and J.-i. Song, Optimization of plastic injection molding process parameters for manufacturing a brake booster valve body. Materials & Design (1980-2015), 2014. 56: p. 313-317.
[10] Zhang, J., et al., Multiobjective optimization of injection molding process parameters based on Opt LHD, EBFNN, and MOPSO. The International Journal of Advanced Manufacturing Technology, 2016. 85(9): p. 2857-2872.
[11] Kitayama, S., R. Onuki, and K. Yamazaki, Warpage reduction with variable pressure profile in plastic injection molding via sequential approximate optimization. The International Journal of Advanced Manufacturing Technology, 2014. 72(5-8): p. 827-838.
[12] Xu, Y., et al., Optimization of injection molding process parameters to improve the mechanical performance of polymer product against impact. The International Journal of Advanced Manufacturing Technology, 2015. 76(9-12): p. 2199-2208.
[13] Sadeghi, B., A BP-neural network predictor model for plastic injection molding process. Journal of materials processing technology, 2000. 103(3): p. 411-416.
[14] Yarlagadda, P.K. and C.A.T. Khong, Development of a hybrid neural network system for prediction of process parameters in injection moulding. Journal of Materials Processing Technology, 2001. 118(1-3): p. 109-115.
[15] Chen, Z. and L.S. Turng, A review of current developments in process and quality control for injection molding. Advances in Polymer Technology: Journal of the Polymer Processing Institute, 2005. 24(3): p. 165-182.
[16] Shi, F., et al., Optimisation of plastic injection moulding process with soft computing. The International Journal of Advanced Manufacturing Technology, 2003. 21(9): p. 656-661.
[17] Bourdon, K. The selection and setting of injection molding machines by means of process simulation. in Annual Technical Conference (ANTEC-1989). 1989.
[18] Duverlie, P. and J. Castelain, Cost estimation during design step: parametric method versus case based reasoning method. The international journal of advanced manufacturing technology, 1999. 15(12): p. 895-906.
[19] Mok, S., C.K. Kwong, and W. Lau, Review of research in the determination of process parameters for plastic injection molding. Advances in Polymer Technology: Journal of the Polymer Processing Institute, 1999. 18(3): p. 225-236.
[20] Murakami, T., T. Okamura, and N. Tanizaki, An operation assistance system for injection molding machines based on constraints processing. IFAC Proceedings Volumes, 1993. 26(2): p. 455-460.
[21] Nagarsheth, P., An integrated system approach for injection molded plastic parts from design to fabrication. ANTEC'89: Plastics Create a World of Difference, 1989: p. 220-223.
[22] Pandelidis, I. and Q. Zou, Optimization of injection molding design. Part II: Molding conditions optimization. Polymer Engineering & Science, 1990. 30(15): p. 883-892.
[23] Pandelidis, I., Q. Zou, and T. Lingard. Optimization of gate location and operational molding conditions for injection molding. in Proceedings ANTEC. 1988.
[24] Wang, H., X.-Y. Ruan, and X. Zhou, Research on injection mould intelligent cost estimation system and key technologies. The International Journal of Advanced Manufacturing Technology, 2003. 21(3): p. 215-222.
[25] Zhou, H., P. Zhao, and W. Feng, An integrated intelligent system for injection molding process determination. Advances in Polymer Technology: Journal of the Polymer Processing Institute, 2007. 26(3): p. 191-205.
[26] Kwong, C.K. and G. Smith, A computational system for process design of injection moulding: Combining a blackboard-based expert system and a case-based reasoning approach. The International Journal of Advanced Manufacturing Technology, 1998. 14(5): p. 350-357.
[27] Kwong, C.K., G. Smith, and W. Lau, Application of case based reasoning injection moulding. Journal of Materials Processing Technology, 1997. 63(1-3): p. 463-467.
[28] Oliaei, E., et al., Warpage and shrinkage optimization of injection-molded plastic spoon parts for

biodegradable polymers using taguchi, ANOVA and artificial neural network methods. Journal of Materials Science & Technology, 2016. 32(8): p. 710-720.
[29] Tang, S., et al., The use of Taguchi method in the design of plastic injection mould for reducing warpage. Journal of Materials Processing Technology, 2007. 182(1-3): p. 418-426.
[30] Zhang, J., et al., The simulation of the warpage rule of the thin-walled part of polypropylene composite based on the coupling effect of mold deformation and injection molding process. Science and Engineering of Composite Materials, 2018. 25(3): p. 593-601.
[31] Taguchi, G. and S. Konishi, Orthogonal arrays and linear graphs: tools for quality engineering. 1987: American Supplier Institute.
[32] Taguchi, G., E.A. Elsayed, and T.C. Hsiang, Quality engineering in production systems. 1989: McGraw-Hill College.
[33] Huang, M.S. and C.F. Chung, Injection molding and injection compression molding of thin-walled light-guided plates with V-grooved microfeatures. Journal of Applied Polymer Science, 2011. 121(2): p. 1151-1159.
[34] Chang, T.C. and E. Faison III, Shrinkage behavior and optimization of injection molded parts studied by the Taguchi method. Polymer Engineering & Science, 2001. 41(5): p. 703-710.
[35] Oktem, H., T. Erzurumlu, and I. Uzman, Application of Taguchi optimization technique in determining plastic injection molding process parameters for a thin-shell part. Materials & design, 2007. 28(4): p. 1271-1278.
[36] Altan, M., Reducing shrinkage in injection moldings via the Taguchi, ANOVA and neural network methods. Materials & Design, 2010. 31(1): p. 599-604.
[37] Chen, R., H. Lee, and C. Yu, Application of Taguchi's method on the optimal process design of an injection molded PC/PBT automobile bumper. Composite Structures, 1997. 39(3-4): p. 209-214.
[38] Huang, M.-C. and C.-C. Tai, The effective factors in the warpage problem of an injection-molded part with a thin shell feature. Journal of materials processing technology, 2001. 110(1): p. 1-9.
[39] Liao, S., et al., Optimal process conditions of shrinkage and warpage of thin-wall parts. Polymer Engineering & Science, 2004. 44(5): p. 917-928.
[40] Chen, J., et al. Effects of process conditions on shrinkage of the injection-molded part. in ANTEC-CONFERENCE PROCEEDINGS-. 2005.
[41] Karasu, M.K., et al., Improvement of changeover times via Taguchi empowered SMED/case study on injection molding production. Measurement, 2014. 47: p. 741-748.
[42] Chil-Chyuan, K. and L. Hsin-You, Dimensional accuracy optimization of the micro-plastic injection molding process using the Taguchi design method. Materials Science, 2015. 21(2): p. 244-248.
[43] Lin, C.-M. and H.-K. Hsieh, Processing optimization of Fresnel lenses manufacturing in the injection molding considering birefringence effect. Microsystem Technologies, 2017. 23(12): p. 5689-5695.
[44] Sreedharan, J. and A. Jeevanantham, Analysis of shrinkages in ABS injection molding parts for automobile applications. Materials Today: Proceedings, 2018. 5(5): p. 12744-12749.
[45] Yizong, T., Z.M. Ariff, and A.M. Khalil, Influence of processing parameters on injection molded polystyrene using Taguchi method as design of experiment. Procedia engineering, 2017. 184: p. 350-359.
[46] Ramakrishnan, R. and K. Mao, Minimization of shrinkage in injection molding process of acetal polymer gear using Taguchi DOE optimization and ANOVA method. Int. J. Mech. Ind. Technol., 2017. 4(2): p. 72-79.
[47] Mehat, N.M., S. Kamaruddin, and A.R. Othman, Modeling and analysis of injection moulding process parameters for plastic gear industry application. International Scholarly Research Notices, 2013. 2013.
[48] Rizvi, S., A.K. Singh, and G.R. Bhadu, Optimization of tensile properties of injection molded α-nucleated polypropylene using response surface methodology. Polymer Testing, 2017. 60: p. 198-210.
[49] Heidari, B.S., et al., Simulation of mechanical behavior and optimization of simulated injection molding process for PLA based antibacterial composite and nanocomposite bone screws using central composite design. Journal of the mechanical behavior of biomedical materials, 2017. 65: p. 160-176.
[50] Mukras, S.M., H.M. Omar, and F.A. al-Mufadi, Experimental-based multi-objective optimization of injection molding process parameters. Arabian Journal for Science and Engineering, 2019. 44(9): p. 7653-7665.
[51] Khor, C., et al., Multi Response Optimization of Injection Molding Parameters for Artificial Phalanx Bone Using Response Surface Methodology, in Intelligent Manufacturing and Mechatronics. 2021, Springer. p. 863-876.
[52] Guo, W., L. Hua, and H. Mao, Minimization of sink mark depth in injection-molded thermoplastic through design of experiments and genetic algorithm. The International Journal of Advanced Manufacturing Technology, 2014. 72(1-4): p. 365-375.
[53] Kitayama, S., et al., Multi-objective optimization of injection molding process parameters for short cycle time and warpage reduction using conformal cooling channel. The International Journal of Advanced Manufacturing Technology, 2017. 88(5-8): p. 1735-1744.
[54] Kitayama, S., et al., Multi-objective optimization of variable packing pressure profile and process parameters in plastic injection molding for minimizing warpage and cycle time. The International Journal

of Advanced Manufacturing Technology, 2017. 92(9): p. 3991-3999.
[55] Nabila, W., et al. Optimization of warpage on plastic part by using response surface methodology (RSM). in AIP Conference Proceedings. 2019. AIP Publishing LLC.
[56] Kitayama, S. and S. Natsume, Multi-objective optimization of volume shrinkage and clamping force for plastic injection molding via sequential approximate optimization. Simulation Modelling Practice and Theory, 2014. 48: p. 35-44.
[57] Azaman, M., et al., Optimization and numerical simulation analysis for molded thin-walled parts fabricated using wood-filled polypropylene composites via plastic injection molding. Polymer Engineering & Science, 2015. 55(5): p. 1082-1095.
[58] Wen, T., et al., Optimization of processing parameters for minimizing warpage of large thin-walled parts in whole stages of injection molding. Chinese Journal of Polymer Science, 2014. 32(11): p. 1535-1543.
[59] Kc, B., et al., Sisal-glass fiber hybrid biocomposite: Optimization of injection molding parameters using Taguchi method for reducing shrinkage. Composites Part A: Applied Science and Manufacturing, 2016. 83: p. 152-159.
[60] Lotti, C., M. Ueki, and R. Bretas, Prediction of the shrinkage of injection molded iPP plaques using artificial neural networks. Journal of Injection Molding Technology, 2002. 6(3): p. 157.
[61] Chen, C.-S., et al., Optimum design of gas-assisted injection molding. Journal of reinforced plastics and composites, 2005. 24(15): p. 1577-1586.
[62] Song, M., et al., Research on effects of injection process parameters on the molding process for ultra-thin wall plastic parts. Journal of Materials Processing Technology, 2007. 187: p. 668-671.
[63] Gao, Y. and X. Wang, An effective warpage optimization method in injection molding based on the Kriging model. The International Journal of Advanced Manufacturing Technology, 2008. 37(9): p. 953-960.
[64] Gao, Y. and X. Wang, Surrogate-based process optimization for reducing warpage in injection molding. Journal of materials processing technology, 2009. 209(3): p. 1302-1309.
[65] Gao, Y., L.S. Turng, and X. Wang, Adaptive geometry and process optimization for injection molding using the Kriging surrogate model trained by numerical simulation. Advances in Polymer Technology: Journal of the Polymer Processing Institute, 2008. 27(1): p. 1-16.
[66] Yarlagadda, P.K., Development of an integrated neural network system for prediction of process parameters in metal injection moulding. Journal of Materials Processing Technology, 2002. 130: p. 315-320.
[67] Lau, H., et al., Neural networks for the dimensional control of molded parts based on a reverse process model. Journal of Materials Processing Technology, 2001. 117(1-2): p. 89-96.
[68] Kenig, S., et al., Control of properties in injection molding by neural networks. Engineering Applications of Artificial Intelligence, 2001. 14(6): p. 819-823.
[69] Kurtaran, H. and T. Erzurumlu, Efficient warpage optimization of thin shell plastic parts using response surface methodology and genetic algorithm. The International Journal of Advanced Manufacturing Technology, 2006. 27(5): p. 468-472.
[70] Manjunath, P.G. and P. Krishna. Prediction and optimization of dimensional shrinkage variations in injection molded parts using forward and reverse mapping of artificial neural networks. in Advanced Materials Research. 2012. Trans Tech Publ.
[71] Özek, C. and Y.H. Çelık, Calculating molding parameters in plastic injection molds with ANN and developing software. Materials and Manufacturing Processes, 2012. 27(2): p. 160-168.
[72] Wang, R., et al., Evaluation of effect of plastic injection molding process parameters on shrinkage based on neural network simulation. Journal of Macromolecular Science, Part B, 2013. 52(1): p. 206-221.
[73] Shi, H., Y. Gao, and X. Wang, Optimization of injection molding process parameters using integrated artificial neural network model and expected improvement function method. The International Journal of Advanced Manufacturing Technology, 2010. 48(9): p. 955-962.
[74] Chen, W.-C. and S.-W. Hsu, A neural-network approach for an automatic LED inspection system. Expert Systems with Applications, 2007. 33(2): p. 531-537.
[75] Maier, H.R. and G.C. Dandy, Understanding the behaviour and optimising the performance of back-propagation neural networks: an empirical study. Environmental Modelling & Software, 1998. 13(2): p. 179-191.
[76] Yin, F., et al., Back propagation neural network modeling for warpage prediction and optimization of plastic products during injection molding. Materials & design, 2011. 32(4): p. 1844-1850.
[77] Xu, G., Z.-t. Yang, and G.-d. Long, Multi-objective optimization of MIMO plastic injection molding process conditions based on particle swarm optimization. The International Journal of Advanced Manufacturing Technology, 2012. 58(5-8): p. 521-531.
[78] Alam, M., et al., Process planning optimization for the manufacture of injection moulds using a genetic algorithm. International journal of computer integrated manufacturing, 2003. 16(3): p. 181-191.
[79] Deng, Y.-M., Y. Lam, and G. Britton, Optimization of injection moulding conditions with user-definable objective functions based on a genetic algorithm. International journal of production research, 2004. 42(7): p. 1365-1390.
[80] Alam, K. and M.R. Kamal, Runner balancing by a direct genetic optimization of shrinkage. Polymer

Engineering & Science, 2004. 44(10): p. 1949-1959.
[81] Zhai, M., Y.C. Lam, and C.K. Au, Runner sizing in multiple cavity injection mould by non-dominated sorting genetic algorithm. Engineering with Computers, 2009. 25(3): p. 237-245.
[82] Ding, L., et al., Multi-objective performance design of injection molding machine via a new multi-objective optimization algorithm. International journal of innovative computing, Information and control, 2011. 7(7): p. 3939-3949.
[83] 83. Chen, C.-C., et al., Experimental investigation of designed parameters on dimension shrinkage of injection molded thin-wall part by integrated response surface methodology and genetic algorithm: A case study. Materials and Manufacturing Processes, 2011. 26(3): p. 534-540.
[84] Zhao, P., et al., Process parameters optimization of injection molding using a fast strip analysis as a surrogate model. The International Journal of Advanced Manufacturing Technology, 2010. 49(9-12): p. 949-959.
[85] Gholami, M.H. and M.R. Azizi, Constrained grinding optimization for time, cost, and surface roughness using NSGA-II. The International Journal of Advanced Manufacturing Technology, 2014. 73(5-8): p. 981-988.
[86] Bouacha, K. and A. Terrab, Hard turning behavior improvement using NSGA-II and PSO-NN hybrid model. The International Journal of Advanced Manufacturing Technology, 2016. 86(9): p. 3527-3546.
[87] Li, K., et al., Warpage optimization of fiber-reinforced composite injection molding by combining back propagation neural network and genetic algorithm. The International Journal of Advanced Manufacturing Technology, 2017. 90(1-4): p. 963-970.
[88] Chen, W.-L., C.-Y. Huang, and C.-Y. Huang, Finding efficient frontier of process parameters for plastic injection molding. Journal of Industrial Engineering International, 2013. 9(1): p. 1-11.
[89] Chen, W.-C., P.-H. Liou, and S.-C. Chou, An integrated parameter optimization system for MIMO plastic injection molding using soft computing. The International Journal of Advanced Manufacturing Technology, 2014. 73(9): p. 1465-1474.
[90] Hazwan, M., et al. Warpage optimization on battery cover using genetic algorithm (GA). in AIP Conference Proceedings. 2019. AIP Publishing LLC.
[91] Li, K., et al., Multi-objective optimization of the fiber-reinforced composite injection molding process using Taguchi method, RSM, and NSGA-II. Simulation Modelling Practice and Theory, 2019. 91: p. 69-82.
[92] Najihah, S., et al. Analysis of shrinkage on thick plate part using genetic algorithm. in MATEC Web of Conferences. 2016. EDP Sciences.
[93] Lam, Y., et al., An evolutionary approach for cooling system optimization in plastic injection moulding. International journal of production research, 2004. 42(10): p. 2047-2061.
[94] Li, D., et al., A real-time process optimization system for injection molding. Polymer Engineering & Science, 2009. 49(10): p. 2031-2040.
[95] Zhang, R., et al., GA based predictive functional control for batch processes under actuator faults. Chemometrics and Intelligent Laboratory Systems, 2014. 137: p. 67-73.
[96] Li, K., et al., Optimization of fiber-orientation distribution in fiber-reinforced composite injection molding by Taguchi, back propagation neural network, and genetic algorithm–particle swarm optimization. Advances in Mechanical Engineering, 2017. 9(9): p. 1687814017719221.
[97] Chen, W.-C., et al., Optimization of the plastic injection molding process using the Taguchi method, RSM, and hybrid GA-PSO. The International Journal of Advanced Manufacturing Technology, 2016. 83(9-12): p. 1873-1886.
[98] Kuo, J.-L. and M.-T. Chang, Multiobjective design of turbo injection mode for axial flux motor in plastic injection molding machine by particle swarm optimization. Mathematical Problems in Engineering, 2015. 2015.
[99] Xu, G. and Z. Yang, Multiobjective optimization of process parameters for plastic injection molding via soft computing and grey correlation analysis. The International Journal of Advanced Manufacturing Technology, 2015. 78(1-4): p. 525-536.
[100] Bensingh, R.J., et al., Injection molding process optimization of a bi-aspheric lens using hybrid artificial neural networks (ANNs) and particle swarm optimization (PSO). Measurement, 2019. 134: p. 359-374.
[101] Tian, M., et al., Multi-objective optimization of injection molding process parameters in two stages for multiple quality characteristics and energy efficiency using Taguchi method and NSGA-II. The International Journal of Advanced Manufacturing Technology, 2017. 89(1-4): p. 241-254.
[102] Kim, H.-G., et al., Optimization and analysis of reaction injection molding of polydicyclopentadiene using response surface methodology. Korean Journal of Chemical Engineering, 2017. 34(7): p. 2099-2109.
[103] Park, H.S. and T.T. Nguyen, Optimization of injection molding process for car fender in consideration of energy efficiency and product quality. Journal of Computational Design and Engineering, 2014. 1(4): p. 256-265.
[104] Sahu, R., D. Yao, and B. Kim. Optimal mold design methodology to minimize warpage in injection molded parts. 1997. TECHNICAL PAPERS OF SPE ANTEC ANNUAL TECHNICAL CONFERENCE.
[105] 105. Mok, S., C.K. Kwong, and W. Lau, A hybrid neural network and genetic algorithm approach to the determination of initial process parameters for injection moulding. The International Journal of Advanced Manufacturing Technology, 2001. 18(6): p. 404-409.

[106] Ribeiro, C. and J. Viana, Optimization of injection moulded polymer automotive components. New trends and developments in automotive system engineering, 2011: p. 65.
[107] Chen, W.-C., et al. A systematic optimization approach in the MISO Plastic Injection molding process. in 2008 IEEE International Conference on Service Operations and Logistics, and Informatics. 2008. IEEE.
[108] Chen, W.-C., et al., Process parameter optimization for MIMO plastic injection molding via soft computing. Expert Systems with Applications, 2009. 36(2): p. 1114-1122.
[109] Shen, C., L. Wang, and Q. Li, Optimization of injection molding process parameters using combination of artificial neural network and genetic algorithm method. Journal of materials processing technology, 2007. 183(2-3): p. 412-418.
[110] Tzeng, C.-J., et al., A study of optimization of injection molding process parameters for SGF and PTFE reinforced PC composites using neural network and response surface methodology. The International Journal of Advanced Manufacturing Technology, 2012. 63(5-8): p. 691-704.
[111] Yen, C., et al., An abductive neural network approach to the design of runner dimensions for the minimization of warpage in injection mouldings. Journal of Materials Processing Technology, 2006. 174(1-3): p. 22-28.
[112] Chen, W., et al., Multi-objective optimal approach for injection molding based on surrogate model and particle swarm optimization algorithm. Journal of Shanghai Jiaotong University (Science), 2010. 15(1): p. 88-93.
[113] Alvarado Iniesta, A., J.L. García Alcaraz, and M. Rodríguez Borbón, Optimization of injection molding process parameters by a hybrid of artificial neural network and artificial bee colony algorithm. Revista Facultad de Ingeniería Universidad de Antioquia, 2013(67): p. 43-51.
[114] Lu, N.-y., et al., Multi-objective process parameter optimization for energy saving in injection molding process. Journal of Zhejiang University SCIENCE A, 2012. 13(5): p. 382-394.
[115] Mohan, M., M. Ansari, and R.A. Shanks, Review on the effects of process parameters on strength, shrinkage, and warpage of injection molding plastic component. Polymer-Plastics Technology and Engineering, 2017. 56(1): p. 1-12.
[116] Wang, X., et al., Pressure analysis of dynamic injection molding and process parameter optimization for reducing warpage of injection molded products. Polymers, 2017. 9(3): p. 85.
[117] Wang, X., et al., Warpage optimization with dynamic injection molding technology and sequential optimization method. The International Journal of Advanced Manufacturing Technology, 2015. 78(1-4): p. 177-187.
[118] Li, H., et al., Multi-objective optimizations for microinjection molding process parameters of biodegradable polymer stent. Materials, 2018. 11(11): p. 2322.
[119] Li, S., et al., Optimization of Injection Molding Process of Transparent Complex Multi-Cavity Parts Based on Kriging Model and Various Optimization Techniques. Arabian Journal for Science and Engineering, 2021: p. 1-11.
[120] Zhao, P., et al., Optimization of injection-molding process parameters for weight control: converting optimization problem to classification problem. Advances in Polymer Technology, 2020. 2020.
[121] Zhao, P., et al., A nondestructive online method for monitoring the injection molding process by collecting and analyzing machine running data. The International Journal of Advanced Manufacturing Technology, 2014. 72(5-8): p. 765-777

DOI: https://doi.org/10.15379/ijmst.v10i2.3754