Journal of Theoretical and Applied Information Technology
15th February 2023. Vol.101. No 3

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

PERFORMANCE ANALYSIS OF PLASTIC INJECTION MOLDING USING PARTICLE SWARM BASED MODIFIED SEQUENTIAL QUADRATIC PROGRAMMING ALGORITHM MULTI OBJECTIVE OPTIMIZATION MODEL

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ABSTRACT

Plastic Injection Molding (PIM) is one among the trending technology which is used in maximum of the plastics based industrial applications. The functionalities of PIM are material insertion, melting, injection, molding closing, mold ejection and cooling. Several variables are involved in the process of molding such as melt and mold temperature, melting and injection time, packing pressure and cooling time. In order to achieve high quality, effective performance in terms of maximizing the weld line temperature and reduction of clamping force. To attain this it is very essential to optimize the variable selection during PIM process. For that purpose, in this research Multi Objective Optimization (MOO) is proposed in plastic injection molding which is the combination of Particle Swarm Optimization (PSO) and a Modified Sequential Quadratic Programming Algorithm (MSQPA) as well as finally using the Ant–Lion Optimization algorithm our proposed PSO-MSQPA is compared. The simulation of this process is performed using the software such as CATIA V5 and MATLAB. Through the numerical and simulation evaluation of the proposed PSO-MSQPA approach, the variables are effectively optimized during the process of injection molding that leads to improve the convergence and reduces the bit error rate and that leads to improve the quality by reducing the clamping force of the PIM process.

Keywords: *Plastic Injection Molding (PIM), Multi Objective Optimization (MOO), Particle Swarm Optimization (PSO), Sequential Modified Sequential Quadratic Programming Algorithm (MSQPA), Ant-Lion Optimization Algorithm*

1. INTRODUCTION

Plastic is a cost effective synthetic materials which is used worldwide and it consists of certain unique characteristics such as easy processing, light weight, cost effective to the end-user so that it get attracted by the industries there it play a most leading role in several application such as automotive, home appliances, and healthcare. Plastic Injection Molding (PIM) is developed to produce the specific plastic part in huge quantity by producing the mold in that specific type using polymer processing method. The principle of PIM is that the molten plastic material gets injected to the developed mold after that certain process is carried out such as cooling, solidification and finally ejection [1]. An Injection Molding Machine (IMM) is invented to perform PIM process and it is divided into three sections, they are injection section, mold congregation section and clamping section (ram clamping and toggle clamping). In toggle clamping high speed injection molding is performed where it consists of three different plates such as front plate, middle plate, and tail plate. Using these plates the speed of the process is highly increased which helps the IMM to achieve high accuracy in the process of PIM. The major merits of using the three plate IMM is that easy customization, high accuracy in molding, processing is quick, uniform force allocation and high flexibility [2], [3]. The symmetric structure of the PIM machine is shown in the figure 1.

At the time of the molding process the electronic components holds high stress where it undergoes into High Pressure Forming (HPF) here it has to

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

bear the local deformations. During the process of PIM, primarily the velocity and temperature of plastic melt gets concentrated in terms of achieving high accuracy. The possible verities of thermoplastics which are widely used in the PIM process are Thermoplastic Polypropylene, Thermoplastic Acrylonitrile butadiene Styrene, Thermoplastic polyvinyl chloride, Polycarbonate, Polyethylene, and Polycarbonate [4], [5].

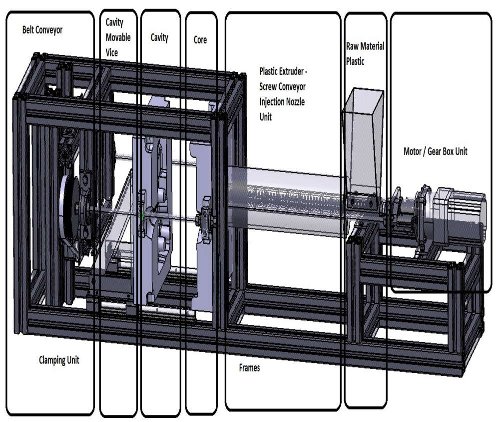

Figure 1: Symmetric structure of the PIM machine

To meet the requirement of the industrial quality it is very essential to find the optimal processing variables for the PIM process and it is in an open research area. Through effective variable selection the consistency of the molding process gets improved and as well the end product becomes high cost effective. On the other hand, the optimization based variable selection is a high challengeable process because if depends on huge factors like molding materials, product plan and the molding process. In terms of industrial requirement, huge quantity and the high quality is the primary requirement of any product in the target. The presence of variables in PIM process is very high that increases the difficulty to achieve the industrial need on time. Achieving high productivity depends on the time taken and as well the quantity of the product with high accuracy. Additional energy consumptions also play a major role in the achievement of high quality and quantity. Also in the earlier research verification several optimization techniques are analyzed which is mainly involved in the implementation of PIM products [6], [7]. Those studies fail to achieve optimal variable selection in the PIM process. Due to improper variable selection process the effectiveness of the process is not fully achieved in the earlier reaches that increase the weight of the end product. In order to reduce the weight of the product in a best manner effective and optimal variable selection is needed. For that purpose, in this paper Practical Scheduling of Plastic Injection Molding is performed using Multi Objective Optimization which is the combination of Sequential Modified Sequential Quadratic Programming Algorithm (MSQPA) and Partial Swarm Optimization (PSO). The contribution of the research is described below.

1.1 Contribution of the Research

• In the earlier researches the parameters which are mainly concentrated in the PIM process are melting temperature, mould temperature, injection pressure, and cooling time. Due to the imperfection in the variable selection the weight of final end project is high which is used in the market. To achieve effective and high quality products with reduced weight it is very essential to perform optimal variable selection. For that purpose in this paper Particle Swarm Optimization (PSO) and a Modified Sequential Quadratic Programming Algorithm (MSQPA) is proposed.

• In the process of PIM the selection of process variable is the critical task. The optimization of the variable becomes very essential to minimize the clamping force during the process of PIM.

• Additionally, the temperature adjustments during the process of PIM and as well the weld lines removal are the major effects.

• For the purpose of effective optimization of the process variable and as well the minimization clamping the multi objective optimization is proposed which is the combination of MSQPA and PSO algorithms.

• To compare the effective of our variable selection process the results are validated with the Ant-Lion Optimization Algorithm. Finally, the effects of the clamping force and weld lines are discussed.

In rest of the article is summarized as below. In section 2, the earlier optimization techniques to minimize the clamping force are discussed. In section 3, the preliminaries such as the PIM process and materials are elaborated. In section 4, the proposed multi objective optimization is detailed. In section 5 the simulation results are analyzed with the PIM machine as well as the proposed method is validated. Finally in the section 6 the conclusion and the future direction are given.

2. RELATED WORKS

In [8], the author Wenjun et.al, Analyze the influence of several SEBS thermoplastic elastomeric materials which is used for the process of experimentation and the filling factor and shape distribution factor are present which is employed to assess the co-injection molding. An optimal co-injection filling effect can also be attained by modifying the injection temperature to alter the dynamic viscosity ratio. The examination of the flow formation and interface interactions of materials can be guided by the dynamic viscosity ratio approach. In [9], the author Maxim et.al, a unique bimetal copper/steel composite was created using copper infiltration and fused filament fabrication. This novel material is the promising one for PIM applications which is aluminum die casting since it has a heat conductivity that is five times higher than tool steel. The production procedure releases design restrictions and permits nearly arbitrary internal cooling channel shapes, which helps to increase the speed of the cycle time and boost the profitability of injection molds.

In [10], the author Azizah Hadny et.al, presented a multi-objective optimization based on entropy weight method. Additionally, BP neural network and particle swarm optimization algorithm is employed for to acquire the best process parameters. This method provides even warpage and shrinkage to the products. In [11], the author Huu That Nguyen et.al, uses response surface methodology (RSM) and particle swarm optimization (PSO) to numerically simulate and multi-objectively optimize an injection molding process for enhancing product quality. The parameter obtained from this technique is to minimize the warpage and residual stress of the products.

In [12], the author CHAO et al developed the fixed factor approach to address the issue of two-goal optimization and significant factor influence differences. This work integrates the Moldex3D flow simulation concerned with many optimization approaches (Methods IV) to identify the processing settings which helps to minimize the OPD and OAD features of plastic Fresnel lenses made when using the ICM process. In [13], the author Chi-Wei Su et al, suggested a standard process to establish the process variables in an approximately optimal manner which is based on the data gathered by the sensors using the adaptive process control system, is. Materials with varying viscosities were used to confirm the viability of the process variables configuration. The coefficient of variation of the weight of product need to get reduced which is the primary task of various viscosity materials, ranging from low to high. In [14], the author Ramkumar et.al utilized the Ratio ranking method to choose a biopolymer (from the specified 9 biopolymers) to be used as charge material for the PIM process based on specific enumerated features, a decision model like MOORA. It was determined that PGA (Poly Glycolic Acid) can be chosen among all options based on the ranking achieved using the method for PIM procedure. In order to produce high quality plastic products, the author [15] Li Qiuli presented a neural network prediction method. Particle swarm optimization is used to predict the process parameters. Through this method, the molding parts of the products are improved. In [16], the author Amsar omiri t.al proposed a hybrid artificial neural network (ANN) and Genetic Algorithm (GA) technique for additive manufacturing's cyber-physical methods to find the product issues. The process of integrating AI frameworks into automated tasks could effectively enhance the manufacturing process.

In [17], the author Huang et. al, investigated the quality of injection-molded parts using an MLP neural network. Additionally, to demonstrate the effectiveness of the proposed technology, an integrated circuit tray was developed. This method enhances the product quality but the manufacturing cost is high.

In [18], the author Bammidi et. al, assess the impact of PIM variables on the molding of PMMA components utilized in the FMCG industry (fast-moving consumer goods). Both statistical and meta-heuristic optimization techniques were used to optimize the control parameters. This will assist FMCG products to produce their goods more quickly and with less waste of raw materials. In [19], the author Maria et.al, designed a coupled PSO-FE thermal management model and optimization to identify ideal Peltier temperature profiles to minimize the disparities in operating temperatures between different cavity features considering their differing wall thicknesses. This will aid in reducing splitting and uneven shrinkage during its sintering process. In [20], the author Kee Jin Lee et.al, proposed an algorithm which conduct unsupervised probability matching between each instance. Here, KNN is employed for optimization process to find the optimal parameters. The proposed algorithm successfully classifies problems across the majority of the evaluation metrics such as meting temperature, packing time.

In [21], the author Bruno Silva et.al, proposed the machine learning methods (Artificial Neural Networks and Support Vector Machines) to prevent Warpage and volume shrinkage faults. The results

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suggest that these methods may recognize the non-linear correlations between the process factors. The ideal factors for enhancing the plastic part quality and lowering energy use have been determined. The plastic components produced using the ideal process parameters had good quality and satisfied the necessary manufacturing standards.

In [22], the author yanick lockner et.al, suggested an Induced network-based transfer learning to carry out a data-driven machine parameter optimization for injection molding processes. The transfer learning method has the potential to considerably increase the applicability of AI techniques for process improvement in the plastics processing sector. The best outcomes are obtained using injection molding source models for components that are identical in the target process.

In [23], the author Huan-Lao Liu et.al utilized the response surface method - central composite experiment design (CCD) integrated with injection molding CAE technology to obtain the optimizing parameters. As a result of PSO optimization, the minimum warpage was lowered by 10.85% when contrasted to the parameters that were earlier optimized.

Table 1: Earlier Study Analysis

Ref.No	Methodology Details	Advantages/Limitation
[8]	Co-injection molding with dynamic viscosity ratio	Enhance filling factor and shape distribution factor. Improper variable selection
[9]	Bimetal copper/steel composite	Enhance the speed of cycle. Overall performed is not cost effective.
[10]	Optimization based on entropy weight method with BP and PSO	Provide even warpage and shrinkage. Weight of the end product is high.
[11]	Response surface methodology (RSM) and particle swarm optimization (PSO)	Reduce the warpage and residual stress. Pressure is high.
[12]	Fixed factor approach	Reduce the OPD and OAD features. Improper variable selection
[13]	Adaptive process control system	Minimum coefficient of variation
[14]	Ratio ranking method	Increase the production. Pressure is high.
[15]	Particle swarm optimization	Enhance product quality. Pressure is high.
[16]	Hybrid artificial neural network (ANN) and (GA)	Enhance the manufacturing process. High time consumption.
[17]	MLP neural network	Enhances the product quality. High energy consumption.
[18]	Statistical and meta-heuristic optimization techniques	Increase the production. Overall performed is not cost effective.
[19]	Coupled PSO-FE thermal management model	Avoid splitting and uneven shrinkage. High delay.
[20]	KNN algorithm	Identify the problems in manufacturing Process.
[21]	Artificial Neural Networks and Support Vector Machines	Reduce Warpage and volume shrinkage.
[22]	Induced network-based transfer learning	Increased product quality. High delay. High energy consumption.
[23]	Response surface method - central composite experiment design	Minimum warpage. Improper variable selection

3. PRELIMINARIES:

3.1 Plastic Injection Molding Working Principles

The process of injection molding is commonly utilized to produce a variety of parts (primarily plastic) and has been adapted to produce components for all kinds of industries. Products range from the finest components to the body panels of machines in a variety of fields, including mechanical engineering, optical engineering, biotechnology, autos, aviation, toys, and residential appliances. During the injection molding process, materials like thermoplastic and thermosetting polymers, fibers, metals, and some mixtures of the aforementioned materials were injected into a helical-shaped screw, under a suitable temperature to pass into the mold. Automated mold design creation can be used to accomplish the high-speed

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

mass production method known as injection molding. The five stages of the injection molding procedures are mold seal, injection, packing, cooling, and open mold. The structure of the proposed counter weight with core and cavity are shown in figure 2.

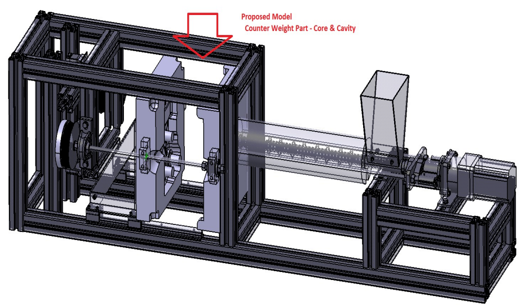

Figure 2: Counter weight with core and cavity

A. Mold Closed- Plastic is injected into the heating cylinder using a funnel and a screwdriver. At this point, the hydraulic system drives the moveable side mold to seal with the stable side mold.

B. Injection - The filling step refers to the procedure where the molten plastic is applied with help of nozzle or through a sprue bushing, runner, or gate to completely occupy the mold chamber.

C. Packing - When the cavity has been stuffed, but the gate has still not hardened to compress the plastic to the mold cavity. The packing stage refers to the act of maintaining a holding pressure to account for material contraction while cooling until the gate solidifies to accommodate for the amount of drawback

D. Cooling - The temperature of plastic present in the mold cavity progressively cools and solidifies in the cavity just after the barrier has become stable because the mold cavity was incapable of fitting the plastic into it. The major coolant required to cool the mold is water that can speed up the cooling process for the components inside the mold.

E. Open mold and detach the plastic components - The mold unlatched and the component is removed by a protector or cover once the part has completely cooled. Then the occurrences were repeated in a loop.

3.2 Injection Molding Material:

The mold which is considered in the injection molding process is creation of plastic counter weight part for the washing machine. At the initial stage the counter weights are created using concrete with stop drum vibration during the process of spin cycle. And as well the weight this concrete counter weight is 25 kg in total which increased the weight of the washing machine up to 65kg. In order to overcome this drawback later on the counter weight are invented in plastic with the weight of 3kg. The weight can be still reduced if we apply a proper optimized valuable selection during molding process. For that purpose in this paper three plastic materials for considered for the injection molding process. They are, Thermoplastic Polystyrene, Thermoplastic Acrylonitrile butadiene Styrene and Thermoplastic polyvinyl chloride. By using effective and optimal variable selection the weight of the plastic counterweight can be reduced below 2 kg which greatly increase the speed of the washing machine.

A. Thermoplastic Polystyrene:

Polystyrene thermoplastic is inexpensive, lighter, and simple to weld, mold, and fabricate. This thermoplastic material is appropriate for a broad range of applications because of its balance of chemical, thermal, and electrical characteristics and desirable strength-to-weight ratio. Polystyrene has very limited gas and water vapor permeability and elevated chemical and solvent resistance. It is therefore widely utilized in the semiconductor sector. It is a wise decision for the food processing sector. It is suitable for areas where bacteria are a problem due to its rigid, high-gloss surface, particularly applications requiring physical food contact. In addition to having superior insulating qualities, Polystyrene also has great arc resistance and dielectric strength, making it a viable option for electrical applications. It can be altered to be anti-static or conducive. The Polystyrene mold is created in PIM machine and it is illustrated in figure 3. From figure it is observed that the weight of the mold is 1.5kg.

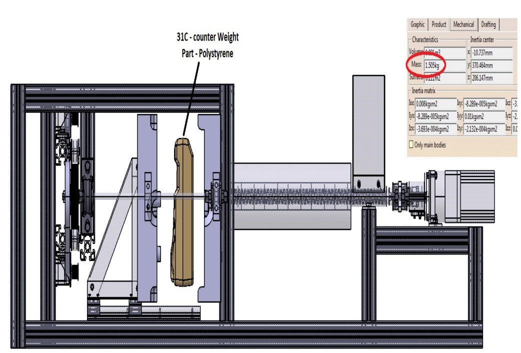

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Figure 3: Polystyrene Mold Creation with counter weight

B. Thermoplastic Acrylonitrile butadiene Styrene:

A common thermoplastic polymer employed during the injection molding process is ABS (Acrylonitrile Butadiene Styrene) plastic. In the creation of 3D printed parts and OEM parts, it is among the most often utilized polymers. A bright, impermeable surface is provided by the styrene content, and exceptional toughness, especially at low temperatures, is provided by the polybutadiene material. Depending on the requirements, it may be possible to change the chemical composition of ABS to enhance particular properties. Because ABS plastic has a chemical composition those results in a lower melting point and a minimum glass transition temperature, it can be conveniently melted down and reshaped using an injection molding process. ABS is reusable because it can be continuously melted down and reformed without suffering substantial chemical deterioration. The ABS mold is created in PIM machine and it is illustrated in figure 4. From figure it is observed that the weight of the mold is 1.7 kg.

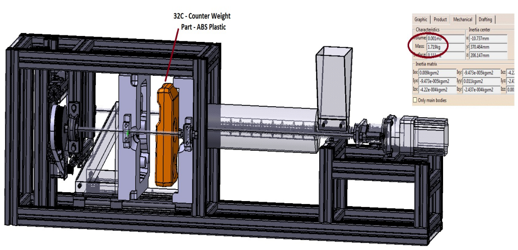

Figure 4: ABC Mold Creation with counter weight

C. Thermoplastic polyvinyl chloride

PVC, often known as polyvinyl chloride, is a common thermoplastic polymer. It's white and fragile till more plasticizers are introduced. The B.F. Goodrich Company employed PVC for the initial time in a business setting in the 1920s. It can be utilized as a flexible material or as a hard polymer, depending on the application. Plasticized PVC is malleable. Home flooring, electrical wire encapsulation, and often used in place of rubber are a few applications for flexible PVC. PVC is most frequently utilized in its rigid form for construction, including vinyl siding for buildings, business equipment housings, and water supply pipelines for plumbing. The PVC mold is created in PIM machine and it is illustrated in figure 5. From figure it is observed that the weight of the mold is 2 kg.

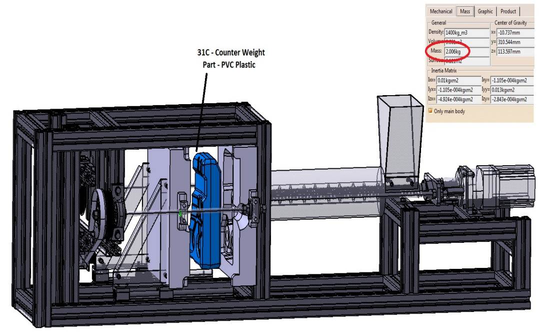

Figure 5: PVC Mold Creation with counter weight

3.3 Injection Molding Process Variables

The fundamental process can be broken down into categories like speed, pressure, time, temperature, and stroke. Since several have an additive impact on the process, the interaction between them is interactive. If the hydraulic back pressure is increased, for instance, the linear screw shrinkage speed (during restoration) results in a screw healing time, melting temperature, and/or symmetric. The product dimensions have changed as a result of variations in the melt temperature, mold filling, operating pressure, mold temperature, product temperature, and heating rate. As a result, the rise in a pressure factor has an overall impact on three other main factors (e.g. hydraulic backpressure). The method and consequent molded parts are most significantly impacted. The relevant process variable must be regulated to rectify the process disturbance when modifications are made to a specific process variable or system configuration (where greatly impacts the resist molding method to generate rejected components). For instance, choosing the inappropriate hopper throat temperature can result in premature molding, which causes the record to change other parameters (such as holding pressure, firing volume, speed filling the mold, etc.) in an attempt to fix the short molding issue. Since the initial decision was erroneous, the process remained unstable, but the molder claims that the issue can be fixed by altering a different kind of variable. However, during production, components that are unsatisfactory and/or inconsistent will still be produced.

3.4 Optimization Protocols Background:

3.4.1 Particle Swarm Optimization Algorithm:

Particle Swarm Optimization (PSO) is motivated by swarm behavior seen in nature, such as fish and bird schooling. PSO simulates a streamlined social structure. The original purpose of PSO algorithm was to graphically recreate the elegant yet unexpected dance of a bird flock. Any bird's viewable range is constrained in nature to a certain area. However, having multiple birds in a swarm enables all of the birds to be conscious of the greater surface of a fitness function. Let's describe the preceding ideas mathematically so that the swarm can locate the global minima of a fitness function.

The main parameters used to model the PSO are:

- $S(n) = \{s1,\ s2, \ldots, sn\}$ is a swarm of n particles
- Si: an individual in the swarm with a position Pi and velocity $Vi.\ i \in |1, n|$
- Pi : the position of a particle Si
- Vi: the velocity of particle Pi
- $pbest$: the best particle solution
- $gbest$: the best swarm solution
- f: fitness function
- $c1, c2$: constant values
- $r1, r2$: random numbers that lies among 0 and 1
- t: iteration number

Mathematical Models:

The PSO algorithm relies on two primary equations. The first equation is the velocity equation, in which each particle in the swarm modifies its velocity based on its current position, the computed values of the individual and global best solutions, and other factors. The acceleration factors associated with the individual and social components are denoted by the coefficients $c\ 1\ and\ c\ 2$.

They are referred to as trust parameters, with c 1 representing a particle's confidence in itself and c 2 modelling a particle's confidence in its neighbours. They define the stochastic impact of thinking and social behaviour along with the random numbers $r\ 1\ and\ r\ 2$:

$$v_i^{t+1} = v_i^t + c_1 r_1 (pbest_i^t - p_i^t) + c_2 r_2 (gbest_i^t - p_i^t) \quad (1)$$

The second equation is a position equation in which each particle updates its position based on the most recent velocity determination:

$$p_i^{t+1} = p_i^t + v_i^{t+1} \quad (2)$$

The dimensions of location and velocity are interdependent, meaning that the position affects the velocity and vice versa.

3.4.2 Sequential Quadratic Programming Algorithm:

A nonlinear constrained optimization problem of the Sequential Quadratic Programming is mathematically expressed in the equation (3),

$$\begin{aligned} &Minimize \quad OF(v) \\ &Subject\ to \quad h(v)=0 \\ &\qquad\qquad g(v) \le 0 \end{aligned} \quad (3)$$

In equation (3) the term $OF(x)$ implies the objective function, v implies the variable, $h(v)\ and\ g(v)$ are the vectors of equality and inequality constraints, accordingly.

The primary concept behind the SQP technique is that the fundamental nonlinear constrained optimization model is transformed into a series of quadratic programming (QP) sub problems that must be resolved, each of which can be written as Eq. (3),

$$Minimize\ QP(d) = [\nabla F(v)]^t d + \frac{1}{2} d^T B d$$
$$Subject\ to\ h(v) + \nabla h(v)^T d = 0$$
$$g(v) + \nabla g(v)^T d \le 0 \quad (4)$$

In equation (4) the term ∇ implies the gradient operator, d implies the search direction of iteration, and B implies the approximate value. The following Broyden-Fletcher-Goldfarb-Shanno (BFGS) formula modifies the hessian matrix:

$$B^{k+1} = B^k - \frac{B^k \delta \delta^T B^k}{\delta^T B^k \delta} + \frac{\delta \delta^T}{\delta^T \gamma} \quad (5)$$

Where

$\delta = v^{k+1} - v, \delta = \nabla L(v^{k+1}, \lambda^k) - \nabla L(v^k, \lambda^k)$

Here $L(v, \lambda)$ is the Lagrange function, k represents the k-th iteration. Start with the initial values of $v^{\circ}, \lambda^{\circ}, and\ B^{\circ}$, the k-th search direction d^k and λ^k can be obtained by solving the Eq.(3). Then a unique, probably minimal point v^{k+1} can be estimated utilizing the following iterative expression.

$$v^{k+1} = v^k + \alpha_v d^k \quad (6)$$

Where α_k is optimal step size in the k-th updated step. The iterative calculation technique described above is continued indefinitely till the appropriate termination criteria is fulfilled,

$$\left|\frac{F(v^{k+1})-F(v^k)}{F(v^k)}\right| \leq \epsilon \qquad (7)$$

Then the optimum point $v^* = v^{k+1}$ for the nonlinear constrained optimization problem is achieved. Based on the properties of gradient descent, the SQP has extremely fast convergence rates, high performance, and effective defense. It has also been demonstrated to be very beneficial at solving constrained optimization issues, and over the recent years, it has been successfully deployed in a variety of engineering fields.

4. MULTI OBJECTIVE OPTIMIZATION IN PIM (MOOPIM):

The idea of MOO is introduced in PIM to optimize the process variables to achieve maximum quality and effectiveness in the process. The proposed approached approach is the combination of two optimization models such as Particle Swarm Optimization (PSO) and a Modified Sequential Quadratic Programming Algorithm (MSQPA). The workflow of the proposed PSO-MSQPA approach is shown in figure 6.

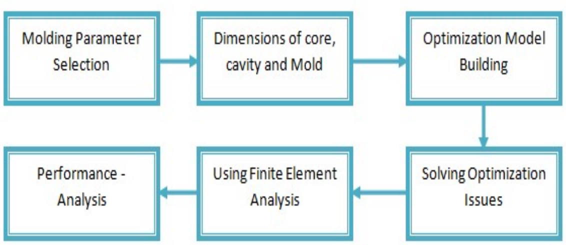

Figure 6: Workflow of the proposed PSO-MSQPA approach

4.1 Optimization for Molding Parameters (P8)

A methodology for enhancing molding variables with direct mathematical optimization model contains an automated modeling approach as well as a schematic approach for direct modeling which is designed using PSO optimization. Multi objective optimization is performed based on PSO and MSQPA models. The direct numerical PSO optimization serves as the foundation for the optimization procedure. Finally the effectiveness is observed using MSQPA model. The predetermined maximal number of simulations is the typical terminating requirement because the computational cost of proffered modeling is often costly for huge and complicated aspects. To enable a faster optimization method, modeling-based optimization employing direct mathematical improvement techniques should be considered. The simulation tool for plastic injection molding (CATIA software) and the programming tool (also known as integration software MATLAB), which is employed to interconnect two tools and address the optimization model, must be coupled to construct the proposed methodology. The implementation software chosen is determined by the appropriate tools and the designer's personal preferences. It is crucial to understand how the optimizer component functions in the suggested architecture.

First, it is decided on the optimal solutions, such as machined surface, shrink, or tensile stress. The developer then determines the design parameters, including limitations, such as the melt temperature, mold temperature, fill time, packing time, and packing pressure. The restrictions are typically the wide variety of design factors and a few boundary criteria associated with the molding system configuration. The simulation is completed to acquire the values of the objective functions. Convergence of the optimization process gets analyzed by considering the outcome of the design variables. The preliminary start point of the mathematical analysis is a crucial aspect in determining the performance of the "optimum solution," among other considerations. Sometimes the amount of iterations is determined by a random beginning start point. However, nobody is aware of the ideal starting point for a search before it even begins. Another issue is that while using a multi objective optimization method, the localized optimum may be attained rather than the global solution. The optimization technique could become stuck at a locally optimal solution if the characteristics of the counter action to the outcome are highly nonlinear. Additionally, the multi objective optimization technique needs much iteration as the number of design factors rises, and the overall simulation expense may be significant. The multi objective optimization technique to achieve best performance molding factors is appropriate for issues with modest simulation costs. Today's high-performance computers can make it easier to apply this optimization technique.

4.2 PSO-MSQPA Approach for the mold:

The associated mold for the core and cavity outlook is illustrated in figure 7. For the purpose of lowering the cost of mold manufacture, the mold in this research has been shrunk to match the real one. The typical dimensions of a mold are 245 mm in length, 155 mm in width, and 70 mm in thickness. In addition, the dimensions of the core and cavity are measured. For the core and cavity it is 310 mm

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

in length, 270 mm in width, and 72 mm in thickness. For cavity it is 245 mm in length, 155 mm in width, and 70 mm in thickness.

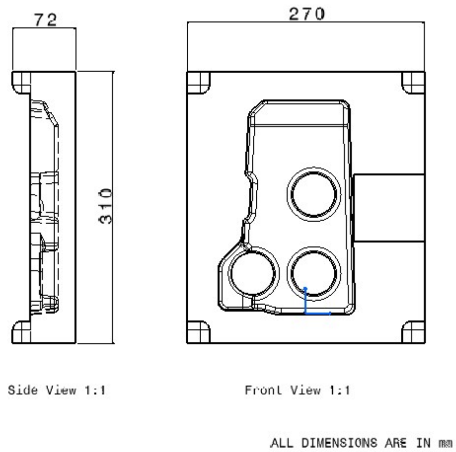

Figure 7(a): Core View

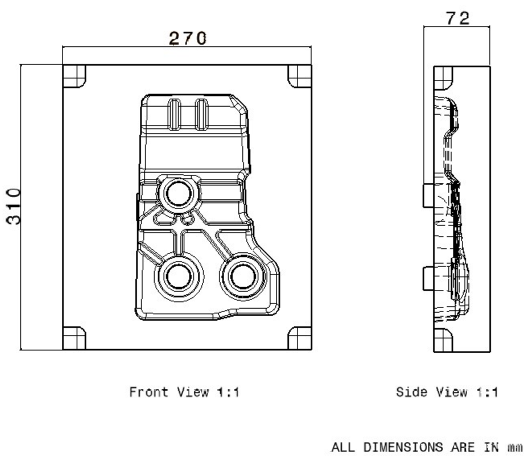

Figure 7(b): Cavity View

Figure 7: The structural view of the core and cavity

4.2.1 Building an optimization model:

It is clear from the aforementioned analysis that improving the heating system in the mold core plate is substantially more challenging. As a result, just the mold core plate was used in the succeeding to illustrate the optimization of the heating system that depends on PSO-MSQPA. Given that such cross section of the mold core plate is almost identical, it makes sense to choose just one of these cross sections as the geometrical model for optimizing, as illustrated in Figure 8. The geometric model did not incorporate the mold cooling channels and other parts that were located below the core plate since they had little bearing on the distribution of core surface temperatures during mold heating. The design of the mold air blowing and ventilation systems in the mold core plate was performed first in order to solve the geometric interference issue.

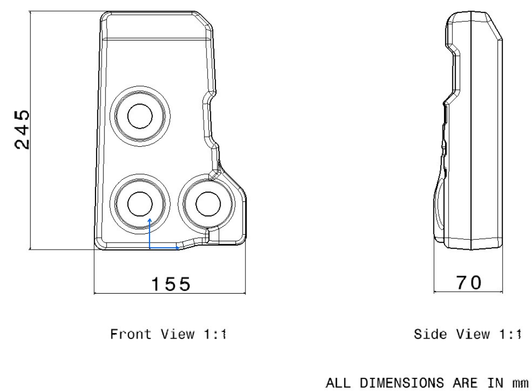

Figure 8: Geometrical Model of Molding

Following that the ABS resin (BM5602, Techno polymer, Japan) utilized in this research is a polymer whose thermal deformation temperature is approximately 120 °C, the entire mold core surface must be heated up to approximately 130 °C in the predefined heating time (denoted as t) in accordance with the requirements of the PSO-MSQPA method. Based on an analysis of heating system optimization for mold cavity plate, the value of t was assumed in this work to just be 30s. As a result, the objective function used to describe the homogeneity of temperature gradient on the core surface is the greatest core surface temperature (designated as T_{CS}) just at time t. It seems that the more regular the temperature gradient on the core surface is, the lesser the value of the T_{CS}, and conversely. Considering the preceding, the optimization model may be written as,

$$\begin{aligned} &Minimize\ T_{CS}(X,P,t) \\ &\qquad Subject\ to\ T_{MCS}(X,P,t) \geq 110℃ \\ &t = 30s \\ &x_i^l \leq x_i \leq x_i^u \\ &15W/cm^2 \leq P_i \leq 30W/cm^2 \\ &(i = 1{\sim}7) \end{aligned} \tag{8}$$

Where $X = [x_1,\ x_2,\ \dots,x_7]$ and $P = [p_1,\ p_2,\ \dots,p_7]$ are the design variables T_{MCS} denotes the minimal core surface temperature at t; x_i^l and x_i^u are, accordingly, the lower and upper bounds of the horizontal vectors.

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4.2.2 Solving the optimization model by PSO-MSQPA

This optimization task can be categorized as being on a medium-scale because Eq. (8) demands for 7 design parameters to be optimized. Building an elevated estimate model to map the mathematical link between objective functions and design parameters relying on alternative models is typically rather challenging in this situation. In order to resolve the optimization technique (see Eq. (8)) within that effort, the explicit mathematical optimization approach integrating MSQPA and PSO was employed. Mold heat transfer process was carried out by the PSO, which also determines the values of the objective functions. MSQPA was utilized as the optimization method to find the ideal design specifications. By combining MATLAB® and CATIA® with programming language and analytic parameter optimization language, the MSQPA and PSO were merged. The optimization process and problem-solving technique can be facilitated by this integrated program, which was run automatically.

The mold is made of P20 steel, which has the following properties: thermal conductivity of 39.4 W/(m°C), density of 7850 kg/m3, and specific heat of 460 J/(kg°C), correspondingly. The baseline and boundary constraints in the modeling also include: (1) The ignition temperature of the mold core tray is the same as the atmospheric temperature of 30 °C; (2) The exchange of heat between the mold external surface and the atmosphere originally belonged to air free convection, and the convection heat transfer coefficient is establish to be 15 W/(m2 °C). Once all of the parameters have been established, the mold heat transfer modeling can be run, and it will be simple to determine the temperature distribution on the mold core surface at 30 seconds for various combinations of design parameters.

4.4 Validation Using Ant-lion Optimization:

Seyedali Mirjalili introduced the Ant Lion Optimizer (ALO), a brand-new technique that was inspired by nature, in 2015. (ALO). The ALO is made to resemble the way ant lions hunt in the wild. An ant lion larva excavates a cone-shaped trench in the soil with its enormous mouth by travelling in circular patterns and dumping sand into the trench. The larva shelters underneath the bottom of the cone after it has been carved and awaits for the bugs to be captured in the ditch in in order to avoid getting consumed by them Insects can easily fall through the trap and into the bottom due to the cone's sharp edge. It first detects the trap, then realizes there is a target in it, and tries to capture it. After that, it is dragged beneath the ground and eaten. Ant lions dispose of their dead prey outside the trench once they have finished devouring them and utilize them to get ready for the next hunt. The pseudo code for the ALO algorithm is described below.

Step 1: The first steps involve initializing the ant and ant-lion populations and calculating their fitness.

Step 2: The best ant lions are sought after and regarded as having outstanding skills.

Step 3: Select appropriate ant lion from the wheel choice for each ant by utilizing the Roulette wheel option for that ant.

Step 4: The load flow is performed out, and each ant's fitness is calculated.

Step 5: The elite will be upgraded if an ant lion proven to be more physically fit than the present group.

Step 6: Until the stopping criteria is achieved, repeat steps 3 through 6; after that, stop.

5. EXPERIMENTAL RESULTS

In this section the experimental results of the proposed PSO-MSQPA is analyzed. In order to solve the optimization problem of the variables the proposed PSO-MSQPA methods employs certain objective functions. The software which is used for the process of experimentation is CATIA and MATLAB R2021b. In CATIA, the materials which are considered for the plastic injection molding process are chosen such as thermoplastic polystyrene, thermoplastic acrylonitrile butadiene styrene and thermoplastic polyvinyl chloride. Using these materials the weight of the plastic counterweight of the washing machine is reduced in the CATIA software. In the final design output the counterweight of the thermoplastic polystyrene is 1.5kg, thermoplastic acrylonitrile butadiene styrene is 1.7kg, and thermoplastic polyvinyl chloride is 2kg. The analysis is performed on MATLAB. TO perform the comparative analysis the results are compared with the earlier optimization technique called AntLion optimization in PIM [18]. The input parameters which are considered for the simulation analysis are shown in table 2.

Journal of Theoretical and Applied Information Technology
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ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Table 2: Input Experimental Parameters

Parameters	Values
Melt Temperature (^{0}C)	220 (^{0}C)
Mold Temperature (^{0}C)	55 (^{0}C)
Ambient Temperature (^{0}C)	22 (^{0}C)
Injection Pressure (MPa)	37 (MPa)
Holding Pressure (MPa)	17 (MPa)
Back Pressure (MPa)	8 (MPa)
Cooling Time (Sec)	6 (Sec)
Holding Time (Sec)	6 (Sec)

At the initial stage certain parameters are calculated analysis the proposed performance by using the PSO and MSQPA algorithm. The parameters which are considered are cylinder pressures, barrel piston position, current point, function value and constraint violation. The outputs are graphically represented in figure 9 and 10. The cylinder pressure is calculated for the proposed PSO-MSQPA approach based PIM process. The cylinder pressure of the barrel, injection A and injection B are considered concerned with the time (s). The barrel piston position is also measured and it is concerned with the Time (s). These parameters are illustrated in figure 9.

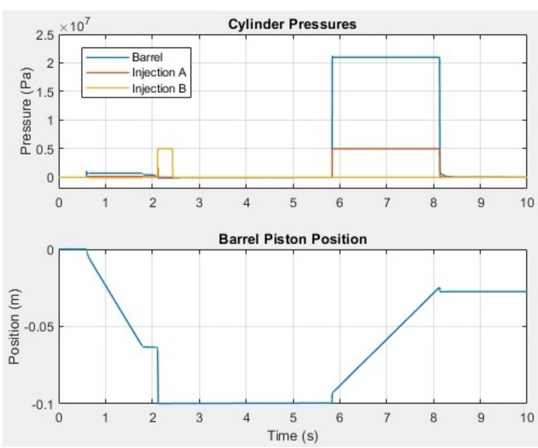

Figure 9: Cylinder Pressures and Barrel Piston Position Calculation

In figure 10 the values of current point, function value and constraint violation is described. The performance of those parameters is calculated concerned with the iteration value.

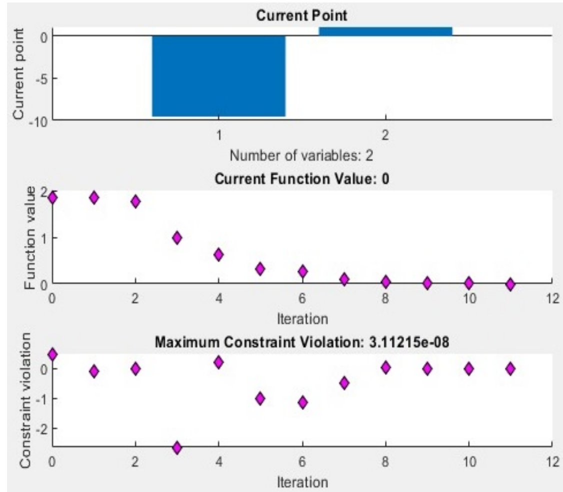

Figure 10: Current Point, Function Value and Constraint Violation Calculation

The parameters which are concentrated for the process of comparative analysis are Bit Error Rate and the Convergence Plot which is illustrated in figure 11 and 12. The bit error rate is calculated for both the method such as PSO-MSQPA and AntLion Optimization. From the results outcome it is understood that the bit error rate of the proposed PSO-MSQPA produced is less than that of the rate produced by the AntLion Optimization and as well that can be achieved with the help of the effective optimization techniques such as PSO and MSQPA.

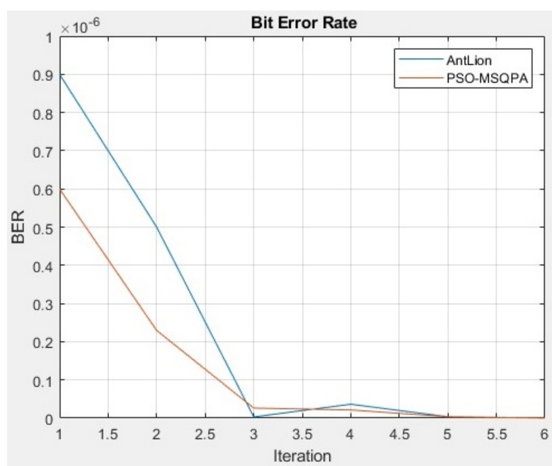

Figure 11: Comparison Bit Error Rate Calculation

In figure 12 the convergence plot is calculated for both the method such as PSO-MSQPA and AntLion Optimization. From the obtained results it gets proven that the convergence plot of the proposed PSO-MSQPA produced is higher than that of the convergence produced by the AntLion Optimization and those values are measured and it is concerned with the iteration count. Achieving higher

Journal of Theoretical and Applied Information Technology
15th February 2023. Vol.101. No 3

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

convergence directly increases the quality of the product. With the help of the proposed PSO-MSQPA the convergence of the product is increased which reflects in the quality improvement of the product.

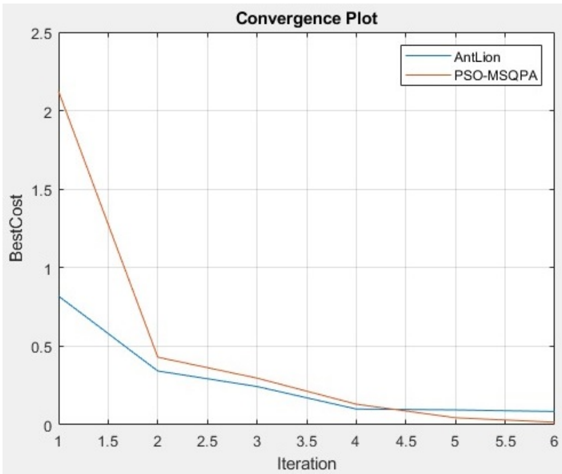

Figure 12: Comparison of Convergence Calculation

According to the aim of the research the weld line width and the clamping force need to get reduced. It is achieved by the optimal selection of molding variables and as well some of the fixed parameters are also present in the proposed PSO-MSQPA. From this convergence calculation it is understood that our proposed method achieves higher possibilities to get optimal variable selection during the process of PIM.

5.1 Termination Criteria of the proposed PSO-MSQPA Approach

The analysis about the termination criteria of the proposed PSO-MSQPA approach is described in table 3. The calculation is performed in terms of the number iteration of the process. The factors which are considered for this analysis are f-CNT, F(x), step, NAC, Max(g), j, KTO, and Max(S).

Table 3: Termination Criteria

Optimization Terminated Successfully from PSO-MSQPA

PSO-MSQPA OutputFcn optimValues

fval: 0.0236

funcCount: 34

gradCount: 11

iterations: 100

constrviolation: 3.1122e-08

Iteration	f-CNT	F(x)	step	NAC	Max (g)	j	KTO
0	3	1.8394	0	2	0.5	1	0.295
1	6	1.8513	1	1	-0.9	1	0.126
2	9	1.7757	1	2	0.01	1	0.267
3	12	0.98387	1	2	-2.6	2	0.714
4	15	0.63429	1	2	0.20	2	0.399
5	18	0.32503	1	2	-0.9	2	0.469
6	22	0.2555	0.19	2	-1.1	2	0.256
7	25	0.0873	1	2	-0.4	1	0.0588
8	28	0.04449	1	2	0.05	1	0.0334
9	31	0.02354	1	2	0.07	2	6.9e-5
10	34	0.02355	1	2	3.11e-08	2	1.41e-2

options: [2 1.0000e-04 1.0000e-06 1.0000e-06 0 0 0 0.0236 0 34 11 34 0 10 20 1.0000e-08 Inf 0]

lambda: [1×1 struct]

5.2 Results Discussion of Proposed PSO-MSQPA

The parameters which are considered for the evaluation of the proposed PSO-MSQPA approach are cylinder pressure, Barrel piston position, current point, current function value and maximum constraint violation. These are parameters are calculation to analysis the behavior of the proposed model. For the process of comparative analysis the parameters which are considered are Bit error rate and convergence and as well the results are compared with the earlier research Ant-Lion optimization based PIM process. From the comparative analysis it is proven that the proposed PSO-MSQPA approach achieves better results when compared with the earlier approaches.

6. CONCLUSION

In this paper to improve the quality of the PIM process, the optimization of variables which are used in the process is concentrated so that the clamping force generation gets reduced which reflects in the increase of the quality of the PIM process. Multi Objective Optimization (MOO) is employed for the process of variables optimization. The variables are effective optimized with the help of the PSO-MSQPA approach. The Major variable which are considered in this PIM process are The injection time, the melt temperature, the mold temperature, the packing time, the packing pressure, the cooling time, and the cooling temperature. The simulation is performed using MATLAB and CATIA. It describes the molded part cooling time with a 35.04 % contribution, melt temperature of 9.22 %, mold temperature of 23.61 %, injection pressure of 2.23 %, holding pressure of 8.01 %, back pressure of 8.34%, holding time of 7.78 %.

This values are compared with the Ant-Lion optimization technique from the analyzing it is observed that the performance of the proposed PSO-MSQPA approach produced 2% high melt temperature, 4% lower mold temperature, 0.29% higher injection pressure, 1.23% lower holding pressure, 2.5% lower back pressure and 1.22% higher holding time when compared with the earlier approach. From the results observed from the comparative analysis it is proved that our proposed PSO-MSQPA approach obtains better performance in terms of bit error rate and convergence when compared with the performance of the Ant-Lion optimization technique. In future direction, to perform defect prediction machine learning algorithm will be concentrated.

REFERENCES:

[1] Morgan, Wani J., and Hsiao-Yeh Chu, "Development of a Reliable Vibration Based Health Indicator for Monitoring the Lubricating Condition of the Toggle Clamping System of a Plastic Injection Molding Machine," Applied Sciences, Vol.12, no. 1, 2021, pp.196, doi: 10.3390/app12010196.

[2] Wang, Jian, and Lu Yang, "Internal circulation clamping system with supplementary volume for small and medium types of two-platen injection molding machine," Advanced Industrial and Engineering Polymer Research, Vol.2, no. 3, 2019, pp. 116-120, doi: 10.1016/j.aiepr.2019.07.003.

[3] Ramorino, Giorgio, Silvia Agnelli, and Matteo Guindani, "Analysis of Reactive Injection Compression Molding by Numerical Simulations and Experiments," Advances in Polymer Technology, vol.2020, 2020, pp. 1-8, doi: 10.1155/2020/1421287.

[4] Langheck, Andreas, Steffen Reuter, Oleg Saburow, Robert Maertens, Florian Wittemann, Lars Fredrik Berg, and Martin Doppelbauer, "Evaluation of an integral injection molded housing for high power density synchronous machines with concentrated single-tooth winding," 2018 8th International Electric Drives Production Conference (EDPC), 2018, pp. 1-6, doi: 10.1109/EDPC.2018.8658324.

[5] Schirmer, Julian, Marcus Reichenberger, Annette Wimmer, Herbert Reichel, Simone Neermann, and Jörg Franke, "Evaluation of Mechanical Stress on Electronic Assemblies During Thermoforming and Injection Molding for Conformable Electronics," 2021 14th International Congress Molded Interconnect Devices (MID), 2021, pp. 1-8, doi: 10.1109/MID50463.2021.9361624.

[6] Dhutekar, Prashant, Girish Mehta, Jayant Modak, Sagar Shelare, and Pramod Belkhode, "Establishment of mathematical model for minimization of human energy in a plastic moulding operation," Materials Today: Proceedings, Vol. 47, 2021, pp. 4502-4507, doi: 10.1016/j.matpr.2021.05.330.

[7] Kumar, B. Prasad, P. Venkataramaiah, and J. Siddi Ganesh, "Optimization of process parameters in injection moulding of a polymer composite product by using gra," Materials Today: Proceedings, Vol.18, 2019, pp. 4637-4647, doi: 10.1016/j.matpr.2019.07.448.

[8] He, Wenjun, Jian Yang, Yaowei Chen, Puyuan Liu, Chao Li, Mengyuan Xiong, Xinsheng Niu, and Xiaoyan Li, "Study on co-injection molding of poly (styrene-ethylene-butylene-styrene) and polypropylene: Simulation and experiment," Polymer Testing, Vol.108, 2022, pp. 107510, doi: 10.1016/j.polymertesting.2022.107510.

[9] Seleznev, Maxim, and Joseph D. Roy-Mayhew, "Bi-metal composite material for plastic injection molding tooling applications via fused filament fabrication process," Additive Manufacturing, Vol. 48, 2021, pp. 102375, doi: 10.1016/j.addma.2021.102375.

[10] Kitayama, Satoshi, Kanako Tamada, Masahiro Takano, and Shuji Aiba, "Numerical optimization of process parameters in plastic injection molding for minimizing weldlines and clamping force using conformal cooling channel," Journal of Manufacturing Processes, Vol. 32, 2018, pp. 782-790, doi: 10.1016/j.jmapro.2018.04.007.

[11] Kitayama, Satoshi, Yusuke Yamazaki, Masahiro Takano, and Shuji Aiba, "Numerical and experimental investigation of process parameters optimization in plastic injection molding using multi-criteria decision making," Simulation Modelling Practice and Theory, Vol. 85, 2018, pp. 95-105, doi: 10.1016/j.simpat.2018.04.004

[12] Lin, Chao-Ming, and Ting-Hsuan Miau, "Optimization of Injection-Compression Molding Processing Conditions for Fresnel Lens Based on Optical Performance and Geometry Deformation Considerations," IEEE Access, Vol. 10, 2022, pp. 65401-65413, doi: 10.1109/ACCESS.2022.3184320.

[13] Su, Chi-Wei, Wei-Jie Su, Feng-Jung Cheng, Guan-Yan Liou, Sheng-Jye Hwang, Hsin-Shu Peng, and Hsiao-Yeh Chu, "Optimization process parameters and adaptive quality monitoring injection molding process for materials with different viscosity," Polymer Testing, Vol.109, 2022, pp. 107526, doi: 10.1016/j.polymertesting.2022.107526.

[14] Ramkumar, P. L., Nikita Gupta, and Aman Shukla, "Bio-polymer selection for injection molding process using Multi Objective Optimization by Ratio Analysis method," Materials Today: Proceedings, Vol. 45, 2021, pp. 4447-4450, doi: 10.1016/j.matpr.2020.12.820.

[15] Guo, Wei, Feng Deng, Zhenghua Meng, Lin Hua, Huajie Mao, and Jianjun Su, "A hybrid back-propagation neural network and intelligent algorithm combined algorithm for optimizing microcellular foaming injection molding process parameters," Journal of Manufacturing Processes, Vol. 50, 2020, pp. 528-538, doi: 10.1016/j.jmapro.2019.12.020.

[16] Bensingh, R. Joseph, Rajendra Machavaram, S. Rajendra Boopathy, and Chidambaram Jebaraj, "Injection molding process optimization of a bi-aspheric lens using hybrid artificial neural networks (ANNs) and particle swarm optimization (PSO)," Measurement, Vol. 134, 2019, pp. 359-374, doi: 10.1016/j.measurement.2018.10.066.

[17] Ayad, George, and Irene S. Fahim,"A Practical Scheduling Optimizer for Plastic Injection Molding Facilities," 2020 International Conference on Decision Aid Sciences and Application (DASA), 2020, pp. 943-947, doi: 10.1109/DASA51403.2020.9317084.

[18] Ravikiran, Bammidi, Deepak Kumar Pradhan, Siddharth Jeet, Dilip Kumar Bagal, Abhishek Barua, and Sasmita Nayak, "Parametric optimization of plastic injection moulding for FMCG polymer moulding (PMMA) using hybrid Taguchi-WASPAS-Ant Lion optimization algorithm," Materials Today: Proceedings, Vol.56, 2022, pp. 2411-2420, doi: 10.1016/j.matpr.2021.08.204.

[19] Bianchi, Maria Floriana, Andreś A. Gameros, Dragos A. Axinte, Stewart Lowth, Aleksander M. Cendrowicz, and Stewart T. Welch, "Regional temperature control in ceramic injection moulding: An approach based on cooling rate optimisation," Journal of Manufacturing Processes, Vol. 68, 2021, pp. 1767-1783, doi: 10.1016/j.jmapro.2021.06.069.

[20] Chen, Jian-Yu, Kai-Jie Yang, and Ming-Shyan Huang, "Optimization of clamping force for low-viscosity polymer injection molding," Polymer Testing, Vol. 90, 2020, pp. 106700, doi: 10.1016/j.polymertesting.2020.106700.

[21] Cao, Yanli, Xiying Fan, Yonghuan Guo, Sai Li, and Haiyue Huang, "Multi-objective optimization of injection-molded plastic parts using entropy weight, random forest, and genetic algorithm methods," Journal of Polymer Engineering, Vol.40, no. 4, 2020, pp. 360-371, doi: 10.13039/501100001809.

[22] Singh, Gurjeet, M. K. Pradhan, and Ajay Verma, "Multi Response optimization of injection moulding Process parameters to reduce cycle time and warpage," Materials Today: Proceedings, Vol. 5, no. 2, 2018, pp. 8398-8405, doi: 10.1016/j.matpr.2017.11.534.

[23] Liu, Huan-Lao, Zi-Lin Zhang, Pei-Ming Peng, and Can Liu, "Optimization of Injection Molding Process Parameters for Automotive Brake Plug-in Based on CCD and PSO," International Journal of Materials Science and Applications, Vol.11, no. 4, 2022, pp. 84-94, doi: 10.11648/j.ijmsa.20221104.11.