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# Quality and Defect Prediction in Plastic Injection Molding using Machine Learning Algorithms based Gating Systems and Its Mathematical Models

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**Abstract:** To achieve high quality products from Plastic Injection Molding (PIM) process it is very essential to identify the defective operations in automatic manner which is most challenging task. This paper proposes a Machine Learning (ML) approach to detect the complex faults occurrence during the PIM process. During initial sampling process of molding to achieve high quality and low time consumption it is essential to concentrate on the suitable determination of parameter values by considering the properties of injection molding process. For that purpose, a novel machine learning algorithms based gating system is introduced in PIM (MLGS-PIM). Technical evaluation can be done using simulation which combines the CATIA and MATLAB. Therefore in MLGS-PIM, a holistic approach is introduced to improve and predict the process quality of the parameters which is based on machine learning approaches. The considered machine learning approaches for this process are Artificial Neural Network (ANN) and Support Vector Machine (SVM). This two learning models are combined to achieve high quality under various conditions. Such novel ML based technique helps to increase the quality characteristics of the injection molding process and it is predicted with various parameter values where the simulation data and measurements are handled in an intelligent manner. The materials which are considered in the PIM process are thermoplastic polystyrene, thermoplastic acrylonitrile butadiene styrene and thermoplastic polyvinyl chloride where three types are gating systems are applied with it and consists of 3, 4 and 5 gates and as well the parameters which are measured for the output analysis are sum rate, bit error rate and convergence plot. The results show that the performance of the proposed MLGS-PIM approach significantly increases the performance when compared with the earlier approaches such as AntLion Optimization and PSO-MSQPA.

**Index Terms**: Plastic Injection Molding (PIM), Machine Learning (ML), Artificial Neural Network (ANN), Support Vector Machine (SVM), CATIA and MATLAB.

## I. Introduction

In the world the plastic is one among the extensively used synthetic materials which maintain its unique properties through that the integration of user demanded products are easily produced. At the initial stages in most of the applications metal counterpart are used then after the intervention plastic the weight of the materials are high reduced and as well it is cost effective in the market. These days plastics hold a prevailing role in industrial applications such as healthcare (Medical equipment manufacturing), automotive (machine design), and home appliances etc [1]. More than 90% of the plastic oriented products are produced using the PIM process. The major advantages in PIM process is that through this process huge volumes of plastic products with varying complexity can able to produce in very short duration of time and maximum productivity can be achieved. PIM is a kind of process which consists of certain segmentations like shaping mold, cooled, solidified, and ejected etc. The major parts in the PIM machine is that the injection unit, the mold assembly unit, and the clamping unit [2]. The structure of PIM machine is shown in figure 1.

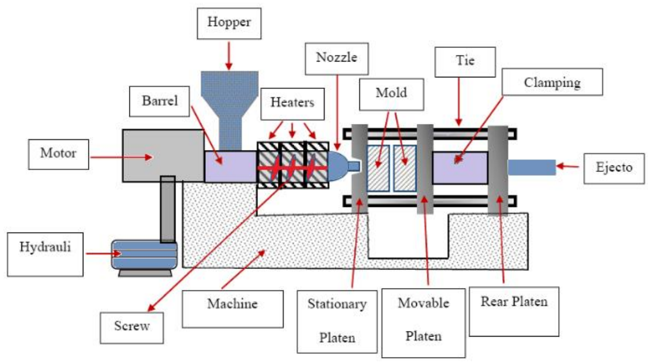


Figure 1 - Structure of PIM Machine

Especially in the field of research, currently quality monitoring becomes very essential in the industrial sector which requires optimal injection molding processing variables selection to achieve high quality in new product

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design and as well in the enhancement of the current products. To improve the product quality in earlier research setting method variables and refining process are used to improve the consistency of the PIM process in molded components [3]. However, it becomes a complex challenge while using the complex combination of materials, variables and the molding system. In the side of industrial sector it requires more adequate and high quality products. Due to the presence of huge number of variables present in the process of PIM the both time and energy consumption occurs in maximum of the cases. So that high quality and productivity is directly proportional to the accurate calculation of the chosen variables [4].

The materials which are considered for the process of making an injection mold has to be sufficient strength, stiffness, wears resistance at the time of thermal conductivity. Some of the materials which are utilized in the process of PIM are Thermoplastic Polystyrene, Thermoplastic Acrylonitrile butadiene Styrene and Thermoplastic polyvinyl chloride [5]. The research mainly concentrated to monitor the quality in a periodical manner and as well to predict the defects during the process of PIM. For that purpose a machine learning model is need to get developed with two branch models [6]. In earlier days several machine learning models are focused on the determination of an optimized mold design using optimum variable selection. Still successful prediction of defects and different measures for the component are in an open research area [7], [8]. The process of machine learning in PIM is illustrated in figure 2.

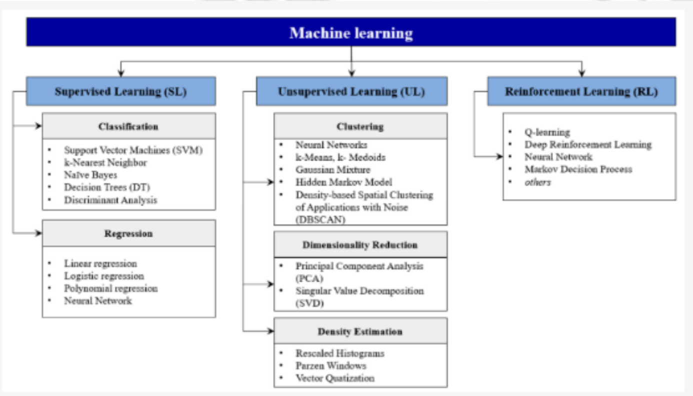


Figure 2 - Process of Machine Learning in PIM

To achieve maximum efficiency, quality and defect prediction in our research, machine learning based approaches are used which is the combination of Artificial Neural Network (ANN) and Support Vector Machine (SVM). Using this two different learning strategies, quality and defect prediction is performed in an effective manner. The contribution of the research is described below.

1.1 Contribution of the research:

- To improve the effective of PIM process machine learning is introduced in it namely machine learning algorithms based gating system (MLGS-PIM).
- To perform effectual optimization is parameters selection in PIM process the machine learning algorithms which are involved in this research are Artificial Neural Network (ANN) and Support Vector Machine (SVM). These two models are combined to achieve high quality under various conditions.
- The materials taken in the PIM process are thermoplastic polystyrene, thermoplastic acrylonitrile butadiene styrene and thermoplastic polyvinyl chloride where three types are gating systems are applied with it and consists of 3, 4 and 5 gates.
- The results show that the performance of the proposed MLGS-PIM increases the performance when compared with the earlier approaches such as AntLion Optimization and PSO-MSQPA.

Rest of the research paper is organized as below. In section 2, the recent machine learning approaches are discussed. In section 3, the preliminaries such as the PIM process, gating system and background of machine learning algorithms are elaborated. In section 4, the proposed MLGA-PIM is discussed with the concept of ISVM and its defect prediction process. In section 5 the simulation experimentations are done with the PIM machine as well as the proposed method is validated with 3 types of gates systems. Finally in the section 6 the conclusion and the future direction are given.

## II. Related Works:

In [9] author Christian.et.al suggested to address the drawbacks of both domains by combining a strategy based on ML from real-world experiments and simulation data. The primary objective is to provide accurate forecasts of product quality from sparse experimental information in order to establish system parameters. However, it is necessary to examine the disparity among simulation and experimental data in order to identify a combined process of learning. In [10] author Josue Obregon et.al., developed a rule-based explanations (RBE) architecture that incorporates a number of machine learning information that can affect to enable us to understand the decision-making processes of complicated and accurate prediction models, particularly tree ensemble models. It only applied to samples of a small size. In [11] the author Kun-Cheng Ke et al proposed a technique that integrates a multilayer perceptron (MLP) neural network model with quality attributes to conduct fast and efficient prediction of final product shape. However, utilizing a subset of indices for model development didn't allow for thorough and superior training. In [12] the author Hail Jung et.al., developed a new variety of machine learning methods to evaluate and compare well the they predicted quality. Significant factors are present and that affect the quality of items produced by injection molding. Therefore, choosing a variable during the molding process is challenging.

In [13] the author Olga et.al, examines the potential use of Artificial Neural Networks (ANN), namely Multi-layered Perceptron (MLP), and Decision Trees, such as J48, to develop models for the process improvement of dog bone specimens made from high density polyethylene. But choosing features is a difficult procedure. In [14] the author Alexander et.al., discusses the many techniques and procedures for feature selection, including filters, wrappers, and embedding approaches, and contrasts the generated feature sets with the attainable goodness of the evaluation methods that were produced utilizing seven different supervised machine learning algorithms for extrapolation. Despite the reasonably strong outcomes the mentioned procedures produced, they have not yet been adopted by industry, even though equivalent goods are available.

In [15] the author alexander et.al, proposed a comprehensive method that automated the necessary data pre-processing processes for seamless part quality prediction. The selected ensemble hyper parameters have a considerable impact on the group performance. In [16] the author Meaghan et.al, proposed technique to bridge the gap between mainstream AI techniques and lower level processes. The method has the benefit of incorporating the complexity brought on by huge data sets into the optimization of automated processes without affecting the amount of time needed for analysis at the cycle level of the process or even the control strategy of the sub processes. In [17] the author Fei Guo et.al developed a decision system based on reinforcement learning combined with an ANN self-prediction model for dynamic optimization in injection molding. The decision model lacks theoretical convergence guarantees when utilizing neural networks as function approximations, and the data is utilized inefficiently. In [18] the author Hong Seok et.al. Focused on control and monitoring in real time. A learning algorithm is established for that function with the intention of creating machine input parameters for proportional correction in sensor readings and, ultimately, the quality of the final product. Although there are various current quality control techniques, using AI will be more advantageous than the traditional ones.

In [19] the author Shailesh et.al, analyzing the process variable data of injection molding processes enables the identification of the essential process variables that can be anticipated by other process variables, emphasizing the interconnection of various process variables in various production scenarios. The information provided by injection molding machines includes run-time, machine setup parameters, and measurements of various process characteristics using sensors. In [20] the author jinsu et.al., provides a complete overview of relatively high surface quality injection molding premised on the electro - optic aspect of surface quality and flaws. Four categories—measuring, affecting factors and causes, prediction, and regulate of surface quality and defects—are used to categories latest advancements and research. Because of the increasing need for big-area injection-molded exterior/appearance parts, surface quality measurement technology for huge areas is required.

## III. Preliminaries

### 3.1 PIM Process and Gating System

In injection molding scheme, through unreasonable selection of uneven filling, uneven cooling, trapped gas, and other parameters leads to certain issues such as warping deformation, fusion marks, volume shrinkage that directly affects the quality of the injection molding process. Due to the process of simulation of injection molding in gating system design those effects can get managed. In this section, the process of gating system design detailed and that results in the increase of accuracy in the PIM process. In order to perform the simulation CATIA software is used where the plastic front-end design is created that satisfies certain requirements like required strength and stiffness, lower weight of the end product. Currently in our product we used plastic other than metal in general when compared with metal, plastic need more space to guarantee maximum stiffness. As well the main concentration is reducing the weight of the end product. The plastic materials which are concentrating on the simulation of plastic injection molding are Thermoplastic Polystyrene, Thermoplastic Acrylonitrile butadiene Styrene and Thermoplastic polyvinyl chloride and the gating system design of those materials consists of the number of gates such as 3, 4 and 5 respectively. All these 3 gate types are applied for all the materials which are used for this PIM process. The CATIA software results of those materials with gated system design are illustrated in the figure 3, 4 and 5.

#### 3.1.1 Gate System Design for Thermoplastic Polystyrene:

In this section the gate positions are analyzed for thermoplastic polystyrene in the sequence of 3, 4 and 5

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gates. The results of the optimal gates positions are shown in figures 3 (a), 3 (b) and 3 (c). Through these figures the distribution of flow resistance indication is performed from highest to the lowest level and as well the optimal gate location is identified using its references. The gates system is implicated by considering the structure of the product and its remolding, exhaust conditions.

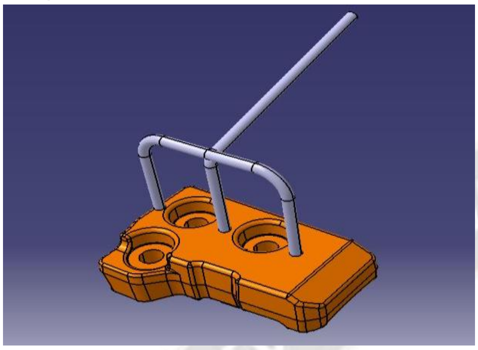

Figure 3 (a) - Gated System Design for Thermoplastic Polystyrene with 3 gates

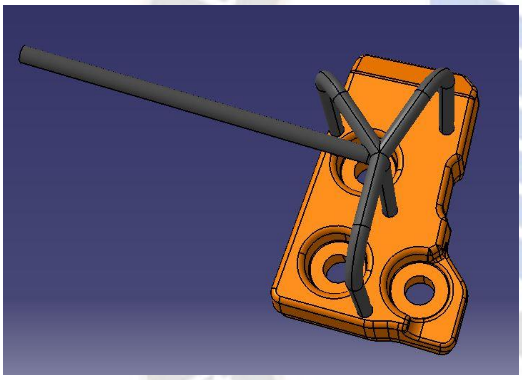

Figure 3 (b) - Gated System Design for Thermoplastic Polystyrene with 4 gates

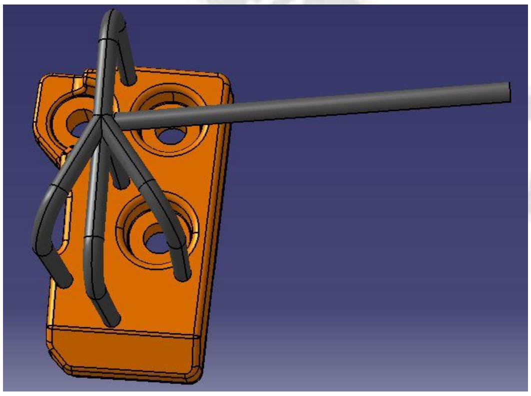

Figure 3 (c) - Gated System Design for Thermoplastic Polystyrene with 5 gates

3.1.2 Gate System Design for Thermoplastic Acrylonitrile Butadiene Styrene:

In this section the gate positions are analyzed for thermoplastic acrylonitrile butadiene styrene in the sequence of 3, 4 and 5 gates. The results of the optimal gates positions are shown in figures 4 (a), 4 (b) and 4 (c).

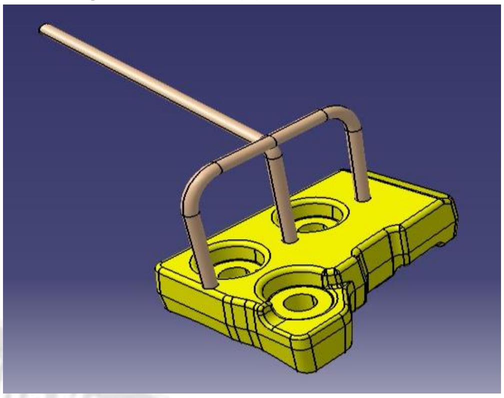

Figure 4 (a) - Gated System Design for Thermoplastic Acrylonitrile butadiene Styrene with 3 gates

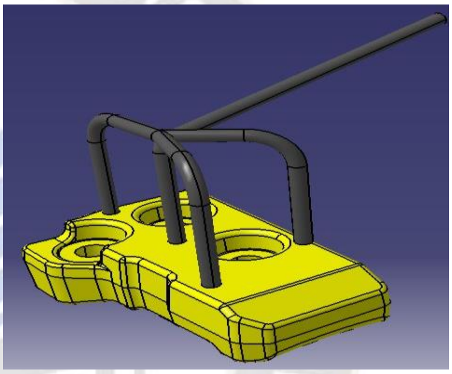

Figure 4 (b) - Gated System Design for Thermoplastic Acrylonitrile butadiene Styrene with 4 gates

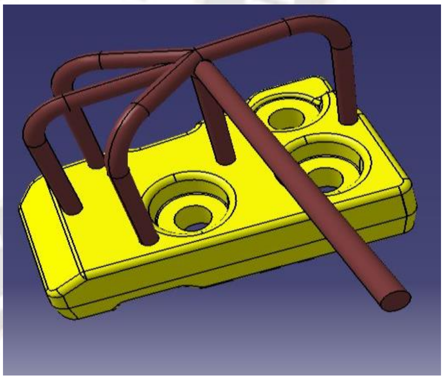

Figure 4 (c) - Gated System Design for Thermoplastic Acrylonitrile butadiene Styrene with 5 gates

3.1.3 Gate System Design for Thermoplastic Polyvinyl Chloride:

In this section the gate positions are analyzed for thermoplastic polyvinyl chloride in the sequence of 3, 4 and 5 gates. The results of the optimal gates positions are shown in figures 5 (a), 5 (b) and 5 (c).

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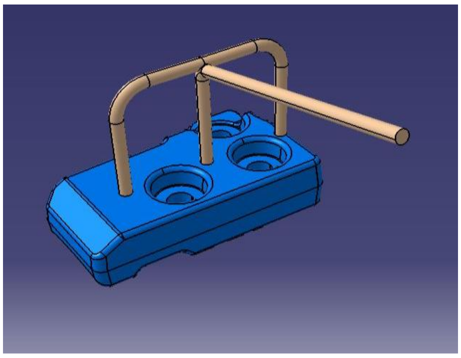

Figure 5 (a) - Gated System Design for Thermoplastic polyvinyl chloride with 3 gates

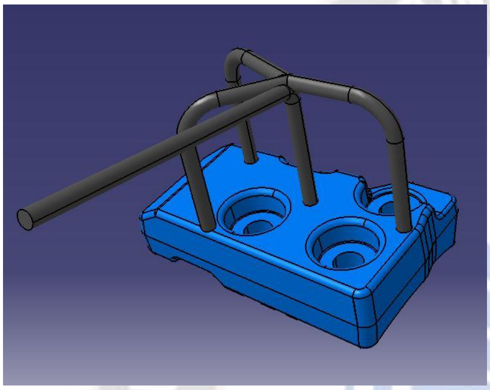

Figure 5 (b) - Gated System Design for Thermoplastic polyvinyl chloride with 4 gates

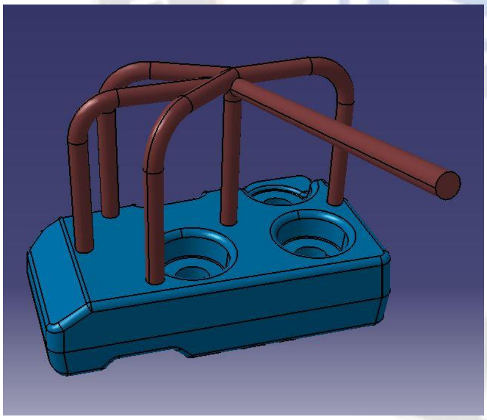

Figure 5 (c) - Gated System Design for Thermoplastic polyvinyl chloride with 5 gates

According to the moldflow in the injection molding the gate positions are analyzed as the results the optimal gate positions are achieved. The model of the washing machine counter weight is developed for all the materials like Thermoplastic Polystyrene, Thermoplastic Acrylonitrile butadiene Styrene and Thermoplastic polyvinyl chloride and detailed according to its properties and as well due to this process the weight of the material can be reduced.

3.2 Background of Machine Learning Algorithms:

The adaptive model selection/weighting methodology makes use of ensemble methods (EM) (Bagging and Boosting) based on DTs, Gaussian process regression (GP), support vector machines (SVM), binary decision trees (DT), and k-nearest neighbors (kNN). In addition, to compare standard statistical methods with machine learning, normal multiple linear regression (MLR) is included in the assessment. Artificial neural network - ANN is an efficient learning algorithm which is utilized in a wide range of applications. They are made up of a single input layer, a single output layer, and one or more hidden layers. Each layer is made up of interconnected neurons that process the input value using an activation function when learning occurs, and the connection weights are updated. Support vector machine - SVMs were originally designed to solve classification challenges. The goal is to develop an ideal hyperplane in n dimensions with the maximum possible margin between the classes. The algorithm was modified using a margin of tolerance for regression issues. Binary decision tree - Utilizing various partition metrics for tree construction, DTs are easy, and simple in understanding. By systematically dividing the data space and reducing the root mean squared error, the models are developed. A "lazy learning" technique called kNN relies on the nearest neighbors in the data space for its output. The (weighted) average value of the neighbors determines the output value for regression problems. Ensemble method - Ensemble techniques incorporate various learning algorithms to improve the predictive performance of a single algorithm. In this study, we emphasize the LSBoost Boosting Method and the Bagging Weighted Synthesis of Several Decision Trees. Gaussian process regression- GPR is a probability distribution over functional possibilities. The Bayes' rule is used to modify the assumption using the training data as reference.

3.2.1 Brief about ANN algorithm:

The application of neural networks (NN) is widely acknowledged in the fields of telecommunication, signal processing, pattern recognition, prediction, process control, and financial analysis. In Addition, Back-propagation neural networks (BPNNs) are widely used in research due to their rapid response and excellent learning accuracy; the supremacy of a network's function approach is determined by network architecture and parameters, as well as the complexities of the problem. The outcomes could be negative if the improper network architecture and parameters are used. In contrast, if proper network architecture and parameters are used, the outcomes will be considerably more valuable. The BPNN is made up of three layers: input, hidden, and output. The BPNN's parameters include factors like learning rate, momentum, the number of hidden layers and neurons. All of these parameters have a substantial effect on the neural network's effectiveness. To ascertain the quantity of hidden layers and neurons, Fogel developed the final information statistic (FIS) approach based on Akaikes' information criterion (AIC). The process of Fogel's research is limited to basic binary categories. Hence, the developed method is to improve AIC, appropriately. These techniques, known as network information criterion (NIC) and neural network information criterion (NNIC), estimate the number of hidden neurons by using statistical probability and an error energy function.

The steepest descent method, also known as the gradient descent learning algorithm, is applied in this work to determine the weight change and to reduce the error energy function. According to previous research, there are some criteria for network learning termination: (1) when the root mean square error (RMSE) between the predicted value and the network target output is minimized to a predefined value; (2) when a certain number of learning cycles have been achieved; the first two approaches are involved with predefined values. This research applies the first and second approaches, steadily increasing the network training time to reduce the root-mean-square error (RMSE) until it is consistent and acceptable.

The following defines the RMSE:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(d_i - y_i)^2} \qquad (1)$$

where $N, d_i,$ and $y_i$ are the quantities representing the number of training samples, the actual value for training sample $i$ and the neural network's expected values for training sample $i$ , accordingly.

The weight values of the network are modified in network learning using input data and output results. The output will conform to the desired outcome more closely if the input training categorization is more specific and more learning information offered. The data must be normalized using the following expression since the learning and validating of data for the BPNN are constrained by the function values:

$$PN = \frac{P - P_{min}}{P_{max} - P_{min}} X\ (D_{max} - D_{min}) + D_{min} \qquad (2)$$

where $PN$ represents normalized data, $P$ for original data, $P_{max}$ for maximum original data value, $P_{min}$ for minimum original data value, $D_{max}$ for expected maximum normalised data value, and $D_{min}$ for expected minimum normalised data value. Finally, The input and output values of the neural network fall between [0.1, 0.9] when applied to the system.

3.2.2 Brief about SVM algorithm: (P18)

This method computes the SVM's regression function. Its main principle is the nonlinear translation of data from the input space to a high - dimensional space. Then, the high-dimensional space is mapped linearly. Set the training sample $\{x_i, y_i\}_{i=1}^{N}, x_i \in R$ as input vector and set $y_i \in R$ as the corresponding export value. $N$ is the number of training sample. The following equation uses SVM regression to predict the unknown function:

$$f(x) = W \times X + b \qquad (3)$$

where X represents the mapped high-dimensional feature space , $w \in R, b \in R$. The risk function can be reduced to coefficients w and b to achieve the following equations:

$$Min\ \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}|y_i - w \times X_i - b| \qquad (4)$$

$$\begin{cases} |y_i - w \times X_i - b| = 0 \\ 0 \le |y_i - w \times X - b| \le \in \\ |y_i - w \times X - b| - \in |y_i - w \times X - b| \le \in \end{cases} \qquad (5)$$

The first component of $\frac{1}{2}\|w\|^2$ in equation (4) is referred to as the model complexity component, while the second component is the empirical error term defined by insensitive loss. The appropriate adjustment parameters are $C$ and $\sigma$. The decision function given by equation (3) can be expressed as scatter data points using the loss function. The direct solution to equation (4) is nearly impossible due to excessive dimensions in feature space and the undifferentiated objective functions. SVM regression method smartly avoids these issues by introducing dot product nuclear function by using the Wolfe antithesis skills, which transforms the identified issues to the following antithesis.

$$\max\ w(a_i, a_i^*) = -\frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N}(a_i - a_i^*)(a_j, a_j^*)$$

$$K(X_i, X_j) - \in \sum_{i=1}^{N}(a_i - a_i^*) + y_i\sum_{i=1}^{N}(a_i - a_i^*) \qquad (6)$$

$$s.t \begin{cases} \sum_{i=1}^{N}(a_i - a_i^*) = 0 \\ a_i - a_i^* \in (0.C) \end{cases}$$

Finally, the simple expression of the relevant regression function equation (7) is as follows:

$$f(x) = \sum_{i=1}^{N}(a_i - a_i^*)K(X_i - X_j) + b \qquad (7)$$

In equation (7), $a$ is Lagrange Multiplier that satisfies the expression: $a_i - a_i^* = 0,\ a_i^* \ge 0, K(X_i - X_i^*)$ is the nuclear function, and its value is inner product of the feature space vectors $X_i$ and $X_j$. The nuclear function may be any function that satisfies the Mercer requirement. The research chooses the RBF nuclear function as follows:

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$$K(X_i - X_j) = \exp\left(-\sigma\|X_i - X_j\|\right)^2 \quad (8)$$

Where $\sigma$ denotes the nuclear parameter. Based on the KKT criteria, training error is more than $\varepsilon$ or equal to $\varepsilon$, and only a portion of coefficient $(a_i - a_i^*)$ is nonzero value. These are support vector samples. Therefore, it entirely determines the regression function.

## IV. Proposed MLGS-PIM Approach:

The proposed MLGS-PIM is designed to achieve effective parameters selection for PIM process. For that purposed the SVM algorithm is shown and it gets improvised with the help of the genetic algorithm and then its defect prediction process. The proposed MLGS-PIM is mainly subdivided into two categories they are, (i) improved-SVM and (ii) defect prediction using ANN-ISVM. The workflow of the proposed MLGS-PIM is shown in figure 6.

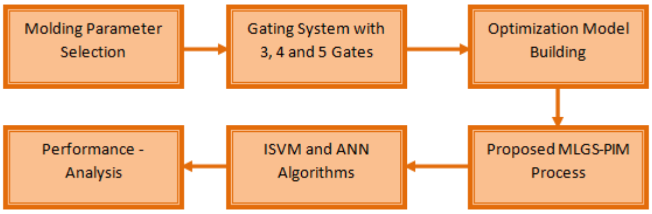


Figure 6 – Workflow of Proposed MLGS-PIM

### 4.1Optimization and Quality Management using Improved-SVM

#### 4.1.1 Back ground of Genetic Algorithm:

Genetic algorithms (GAs) are robust adaptive optimization algorithms that enable an optimal probabilistic search in a high-dimensional space and have been widely employed to find an optimal solution; Tseng. Additionally, GAs is defined as a method of biological evolution. Although the process of evolution is random, it is controlled by a mechanism of selection that is based on the fitness of specific structures. To implement genetic evolutionary theory to a given problem, two difficulties must be discussed: (1) the encoding of an appropriate solution and (2) the best possible fitness function. A chromosome is a vector made up of various parts (genes) that serves as the genetic representation of a solution. The initial population of chromosomes is either created randomly or in accordance with specified standards. The existing population is assessed using the fitness function, and new solutions are then extracted to develop a new population. The new population is created through a variety of GA processes, including selection, crossover, and mutation. Initially, the old population's solutions are chosen based on their fitness; the more suited they are, the greater the probability that they will be chosen. By using crossover and mutation, the chosen solutions creating a pool of parents are then employed to create their infants to generate a new population.

Chromosome representation - The majority of genetic algorithms (GAs) use population-level natural genetics and evolution concept to search for the population's global optimal solutions. The term "string" or "chromosome" refers to each individual in the population that is encoded as a binary string. The existing population produces a new generation of GAs. When using GAs to address the current concerns, a string scheme is used to encode the potential solutions (chromosomes) as symbolic strings.

Fitness function - Genetic algorithms (GAs), which include the basic GA and all of its variants, are computational processes that imitate the process of evolution in nature. Improvements in a species are brought about through the survival of the fittest rule. GAs is heuristic methods, so they cannot be relied upon to always determine the best answer, although they are capable of achieving this for a variety of issues. The fitness of each potential solution is assessed using a fitness function (or objective function). Each member of the population is given a fitness value.

Selection operation - One of the fundamental GA operators that guarantee survival of the fittest is selection. The chosen individuals form pairs known as parents. The selection policy used here is a hybrid of the rotating roulette wheel approach and the elite method. The most successful chromosomes from the current generation can be forced into the upcoming generation using the elite approach. The reproduction gap is evaluated by environmental parameters.

Crossover and mutation operation - The primary operator employed for reproduction is crossover. It combines elements of both parents to produce two new people, known as offspring. In this work, we first choose two crossover points that are sorted randomly. The elements between two crossover points from the selected parent are then passed down to the offspring in the same sequence and arrangement as they occurred in the parent. The remaining components are acquired in the order of their appearance from the alternative parent. This starts with the first position, then moves on to the second crossover point, and then skips through all elements which are already active in the offspring. The crossover procedure is carried out whether or not it is specified by a random value. The clone operation is performed in place of the crossover operation if the value is greater than the crossover rate set in the configuration file of GA parameters. Here, the mutation procedure is performed using the swap method. The swap technique randomly chooses two points to establish the two swapping points of

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the selected parent. If the value is higher than the mutation rate specified in the configuration file for the GA parameters, no mutation is performed and the selected parent is assigned to the new generation without further processing.

4.1.2 ISVM Parameters based Optimization:

The mathematical model of the optimization approach is as follows. Find $X = [x_1, x_2, x_3 \dots\dots, x_n]^T$

$$\text{Min } f(x) = s.t. \begin{cases} x_j^{(l)} \leq x_j \leq x_j^{(u)} \; (j = 1,2 \dots\dots, n) \\ G_i(X) \leq 0 (i = 1,2 \dots\dots, m) \end{cases} \tag{9}$$

Where $f(x)$ is an objective function. $G_i(X)$ denotes constraints $x_j^{(l)}$ and $x_j^{(u)}$ are the lower and upper limits of the design variable $x_j$, accordingly.

The optimal design approach for optimizing nuclear parameters can be described as follows: Find $X = [C\ \sigma]^T$

$$f(x) = s.t. \{ x_j^{(l)} \leq x_j \leq x_j^{(u)} \; (j = 1,2) \tag{10}$$

The optimization problems represented by equation (10) are resolved using the GA method. This work will discuss in detail in the following section. Construction the fitness function - The appropriate fitness function should be developed to assess the performance of the individual string (chromosome). The objective function is typically translated into the fitness function. In this optimization problem, the fitness function $\delta$ can be expressed as,

$$\delta = |f(x)| - f'(x) \tag{11}$$

Where $f(x)$ indicates the training export value of SVM model, and $f'(x)$ denotes the expectation export value of SVM model.

Encoding individual - Optimizing is required for the nuclear parameters C and $\sigma$. The parameter $\sigma$ has a range of 0 to 5, while the parameter C has a range of 1 to 1000. The precision governs the length of the bit string in binary coding method. As a result, the decimal coding method is used in terms of the optimization problem's features.

Operate selection - Determine each person's fitness $f_i$, and then the probability of selecting that person is P as follows:

$$P = \frac{f_i}{\sum f_j} \tag{12}$$

Where $\sum f_j$ is the total of each person's fitness levels. Apply roulette wheel selection to choose the individual based on probability P as a mean.

Operate crossover and mutation - In this paper, Gaussian Mutation and Uniform Crossover are used. Crossover probabilities range from 0.4 to 0.99, and mutation probabilities from 0.001 to 0.1 ranges. In order to compare the GA approach, the optimum nuclear parameters will be determined and analyzed using the conventional cross validation, as shown in Table 1.

Table 1 - Result of nuclear parameters

| Method of Optimization | C | $\sigma$ | Time (min) |
|---|---|---|---|
| Cross validation | 110 | 0.1597 | 96 |
| GA | 101.63 | 0.1666 | 16 |

Table 1 demonstrates that the GA method is more precise and time-consuming than cross validation. As a result, the research will create an SVM forecasting model using the nuclear parameters that GA has optimized.

4.2 Defect Prediction Using ANN-ISVM:

Computer simulation technology makes the mold flow CAE software available to forecast plastic product flaws. To enhance and optimize the processing parameters of plastic products, designers can use the results to modify the process parameters and mould design to prevent incorrect design, thereby lowering manufacturing costs and shortening the new product to market cycle. Typically, STL data from CAD systems are imported into mould flow CAE systems for modeling purposes. To ensure the follow-up analysis, the FEM mesh model needs to be made up and changed. After choosing the type of material, the type of analysis, the injection molding conditions, and the process parameters, designers can make the simulation to produce analysis results. According to the report, designers can determine the root causes of problems, adjust the process parameters, and then repeat analyses until they determine the ideal process parameters. CAE software does not directly deliver the value of output image such as weld lines.

Therefore, dealing with non-quantification data for the optimization of the injection molding process is complicated. As a result, to determine its value, it must be measured in terms of digital image processing. Digital images are a form of spatial coordinates, and the grayscale in them is not consistent (generally integer). It can be applied to a wide range of applications, has high precision handling capabilities, and good reproducibility. It is simple to understand the characteristics of the treatment threshold image when image segmentation is applied in the centre. Images are made up of a bright object and a dark background, dividing the grayscale pixels that make up the object and background into two groups that are each dominated by a different mode. Concentrated extracts from the objects are clearly a method of selection, and these models will be separated. All the points in $f(x, y) > T$ must be greater than or equal to T in order to become the

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target point; otherwise, they will become the background points. How constrained a door handle's options are when dealing with a single threshold. Many limitations on door handles provide a point of classification, when $T_1 < (x, y) \leq T_2$, The point is separated into objects, and is classified as another object. The following function T operations can be tested using threshold as a deal.

$$T = T[x, y, p(x, y), f(x, y)] \quad (13)$$

Since this point is local in nature, it is the average grey level's central region, as indicated by the expression $f(x, y)$. Following application of the threshold, the picture $g(x, y)$ is defined as:

$$g(x, y) = \begin{cases} 1 & f(x, y) > T \\ 0 & f(x, y) \leq T \end{cases} \quad (14)$$

As a result, the background correlates to the pixels designated as 0, and the highlighted pixels belong to one object. Thus the threshold has changed into the overall situation when $T$ just depends on $f(x, y)$. Threshold is partial if $f(x, y)$ and $p(x, y)$ are dependent on $T$. Additionally, the threshold is dynamic or adaptive if T relies on the spatial coordinates x and y.

## V. Experimentations

For the process of experimentation the software's which is used are CATIA and MATLAB R2021b. The experimentation is performed in those software and the results of the MLGS-PIM is analyzed. Optimal Gating system is obtained using 3, 4 and 5 gates for this experimentation and the results are compared with the earlier researches like PSO-MSQPA and AntLion optimization in PIM. In CATIA the analysis is done for the materials like as thermoplastic polystyrene, thermoplastic acrylonitrile butadiene styrene and thermoplastic polyvinyl chloride and for all these materials the gating system is applied. The parameter description for all three materials with 3 gating systems is given in the table 2, 3 and 4.

Table 2 - Parameters Description for Polystyrene

| S. No | Parameter Description | 3 Way | 4 Way | 5 Way |
|---|---|---|---|---|
| 1 | Injection Time (S) | 15 | 9 | 5 |
| 2 | Mold Temp (°C) | 58 | 54 | 50 |
| 3 | Melt Temp (°C) | 240 | 235 | 230 |
| 4 | Packing Pressure(Mpa) | 82 | 63 | 42 |
| 5 | Process Efficiency (%) | 60 | 81 | 96 |
| 6 | Reliability Factor | Low | Medium | High |
| 7 | Process Production Cost (Per 1000Nos) Initial setup + Maintenance | 1.7L | 1.54L | 1.25L |

Table 3 - Parameters Description for PVC

| S. No | Parameter Description | 3 Way | 4 Way | 5 Way |
|---|---|---|---|---|
| 1 | Injection Time (S) | 17 | 11 | 6 |
| 2 | Mold Temp (°C) | 69 | 59 | 57 |
| 3 | Melt Temp (°C) | 260 | 248 | 237 |
| 4 | Packing Pressure(Mpa) | 95 | 78 | 54 |
| 5 | Process Efficiency (%) | 58 | 74 | 91 |
| 6 | Reliability Factor | Low | Medium | High |
| 7 | Process Production Cost (Per 1000Nos) Initial setup + Maintenance | 1.89L | 1.67L | 1.55L |

Table 4 - Parameters Description for Polypropylene

| S. No | Parameter Description | 3 Way | 4 Way | 5 Way |
|---|---|---|---|---|
| 1 | Injection Time (S) | 11 | 8 | 4 |
| 2 | Mold Temp (°C) | 57 | 51 | 50 |
| 3 | Melt Temp (°C) | 236 | 231 | 228 |
| 4 | Packing Pressure(Mpa) | 79 | 61 | 41 |
| 5 | Process Efficiency (%) | 71 | 84 | 97 |
| 6 | Reliability Factor | Low | Medium | High |
| 7 | Process Production Cost (Per 1000Nos) Initial setup + Maintenance | 1.52L | 1.51L | 1.5L |

The analysis is performed in MATLAB and the parameters which are calculated for the performance analysis are sum rate, bit error rate and convergence plot and as well is it calculated for three different iteration scenarios like iteration 10, 20 and 30. The detailed evaluation is described below.

### 5.1 Sum Rate Calculations for varying iterations:

In this section the sum rate of the methods such as AntLion, PSO-MSQPA and proposed MLGS-PIM is calculated for varying iteration such as 10, 20 and 30. Figure 7, 8 and 9 shows the sum rate of the methods which are involved in this process and it values are analyzed in table 5, 6 and 7.

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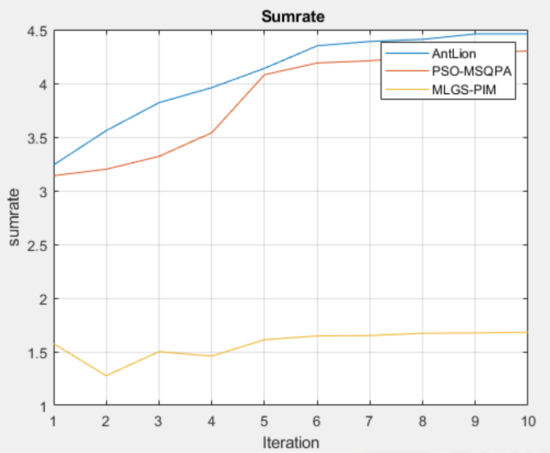


Figure 7 – Sum Rate Calculation for Iteration 10

Figure 7 demonstrate the calculation of sum rate for the iteration of 10 counts and the analyses are performed for the methods like AntLion, PSO-MSQPA and proposed MLGS-PIM. To achieve effective end product it is essential to reduce the sum rate during the PIM process. From the results calculation it is understood that the proposed MLGS-PIM achieved lower sum rate with the help of the effective machine learning algorithm such as improved SVM and ANN. The numerical analysis of the sum rate calculation for 10 iteration counts are given in table 5.

Table 5 - Sum Rate Value Analysis for Iteration 10

| Iteration | AntLion | PSO-MSQPA | MLGS-PIM |
|---|---|---|---|
| 1 | 3.24 | 3.14 | 1.57 |
| 2 | 3.56 | 3.20 | 1.27 |
| 3 | 3.82 | 3.32 | 1.50 |
| 4 | 3.96 | 3.54 | 1.45 |
| 5 | 4.14 | 4.08 | 1.61 |
| 6 | 4.35 | 4.19 | 1.64 |
| 7 | 4.39 | 4.21 | 1.65 |
| 8 | 4.41 | 4.25 | 1.67 |
| 9 | 4.46 | 4.29 | 1.67 |
| 10 | 4.46 | 4.30 | 1.68 |

In this table, the sum rate calculation for the iteration 10 is measured for the methods such as AntLion, PSO-MSQPA and proposed MLGS-PIM. From the table it is proven that the sum rate values of proposed MLGS-PIM is lower than the other methods where sum rate calculation of MLGS-PIM varies from 1.57 to 1.68 where for the earlier methods like AntLion and PSO-MSQPA it varies from 3.24 to 4.46 and 3.14 to 4.30 respectively. So the sum rate is lower for the proposed MLGS-PIM using machine learning algorithms.

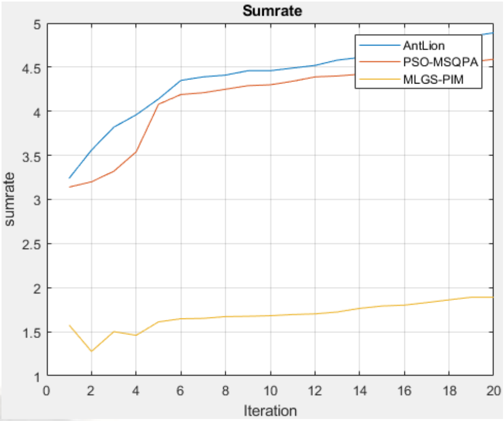


Figure 8 – Sum Rate Calculation for Iteration 20

Figure 8 illustrates the calculation of sum rate for the iteration of 20 counts and the analyses are performed for the methods like AntLion, PSO-MSQPA and proposed MLGS-PIM. Hence achieving lower sum rate is the target to get the effective end results the proposed MLGS-PIM achieved lower sum rate when compared with the earlier researches in PIM and it gets attained using the innovative machine learning algorithm in the MLGS-PIM process. The numerical analysis of the sum rate calculation for 20 iteration counts are given in table 6.

Table 6 - Sum Rate Value Analysis for Iteration 20

| Iteration | AntLion | PSO-MSQPA | MLGS-PIM |
|---|---|---|---|
| 2 | 3.56 | 3.20 | 1.27 |
| 4 | 3.96 | 3.54 | 1.45 |
| 6 | 4.35 | 4.19 | 1.64 |
| 8 | 4.41 | 4.25 | 1.67 |
| 10 | 4.46 | 4.30 | 1.68 |
| 12 | 4.52 | 4.39 | 1.70 |
| 14 | 4.61 | 4.42 | 1.76 |
| 16 | 4.71 | 4.49 | 1.80 |
| 18 | 4.81 | 4.52 | 1.86 |
| 20 | 4.89 | 4.59 | 1.89 |

In this table, the sum rate calculation for the iteration 20 is measured for the methods such as AntLion, PSO-MSQPA and proposed MLGS-PIM. From the table the sum rate calculation of MLGS-PIM varies from 1.27 to 1.89 where for the earlier methods like AntLion and PSO-MSQPA it varies from 3.56 to 4.89 and 3.20 to 4.59 respectively. So the sum rate is lower for the proposed MLGS-PIM when compared with the earlier researches using the algorithms such as ISVM and ANN for optimal parameter selection process.

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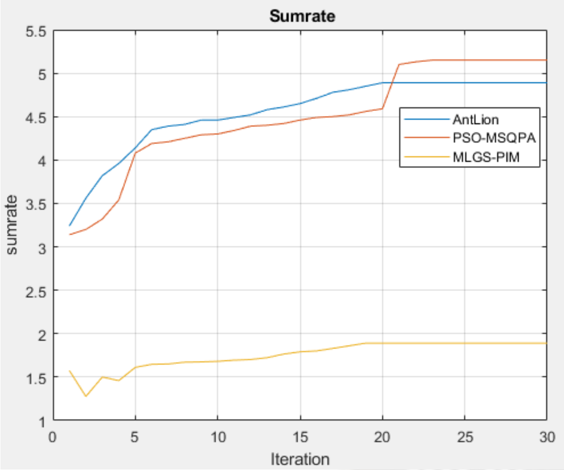


Figure 9 – Sum Rate Calculation for Iteration 30

Figure 9 shows the calculation of sum rate for the iteration of 30 counts and the analyses are performed for the methods like AntLion, PSO-MSQPA and proposed MLGS-PIM. From figure it is proven that the proposed MLGS-PIM produced lower sum rate during the process of PIM where that helps to achieve effective end results which is achieved using the algorithms like ISVM and ANN. The numerical analysis of the sum rate calculation for 30 iteration counts are given in table 7.

Table 7 - Sum Rate Value Analysis for Iteration 30

| Iteration | AntLion | PSO-MSQPA | MLGS-PIM |
|---|---|---|---|
| 3 | 3.82 | 3.32 | 1.50 |
| 6 | 4.35 | 4.19 | 1.64 |
| 9 | 4.46 | 4.29 | 1.67 |
| 12 | 4.52 | 4.39 | 1.70 |
| 15 | 4.65 | 4.46 | 1.79 |
| 18 | 4.81 | 4.52 | 1.86 |
| 21 | 4.89 | 4.52 | 1.86 |
| 24 | 4.89 | 4.52 | 1.86 |
| 27 | 4.89 | 4.52 | 1.86 |
| 30 | 4.89 | 4.52 | 1.86 |

In this table, the sum rate calculation for the iteration 30 is measured for the methods such as AntLion, PSO-MSQPA and proposed MLGS-PIM. From the table the sum rate calculation of MLGS-PIM varies from 1.50 to 1.86 where for the earlier methods like AntLion and PSO-MSQPA it varies from 3.82 to 4.89 and 3.32 to 4.52 respectively. So the sum rate is lower for the proposed MLGS-PIM when compared with the earlier researches.

5.2 Bit Error Rate Calculations for varying iterations:

In this section the bit error rate of the methods such as AntLion, PSO-MSQPA and proposed MLGS-PIM is calculated for varying iteration such as 10, 20 and 30. Figure 10, 11 and 12 shows the bit error rate of the methods which are involved in this process and it values are analyzed in table 8, 9 and 10.

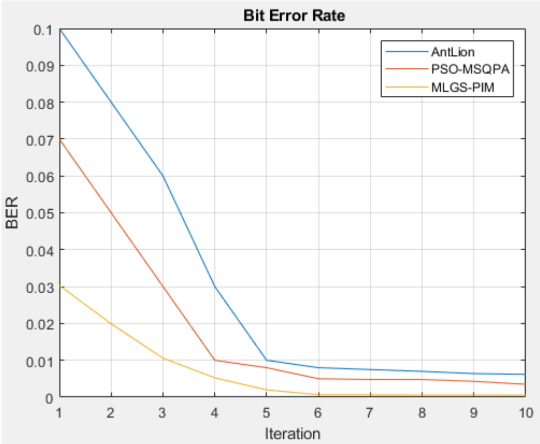


Figure 10 – Bit Error Rate Calculation for Iteration 10

Figure 10 demonstrate the calculation of bit error rate for the iteration of 10 counts and the analyses are performed for the methods like AntLion, PSO-MSQPA and proposed MLGS-PIM. To attain effectual end product it is necessary to decrease the bit error rate at the time of PIM process. From the results it is proven that the proposed MLGS-PIM achieved lower bit error rate using machine learning algorithm such as improved SVM and ANN for the process of optimal parameter selection. The numerical analysis of the bit error rate calculation for 10 iteration counts are given in table 8.

Table 8 - Bit Error Rate Value Analysis for Iteration 10

| Iteration | AntLion | PSO-MSQPA | MLGS-PIM |
|---|---|---|---|
| 1 | 0.1 | 0.07 | 0.030 |
| 2 | 0.08 | 0.05 | 0.019 |
| 3 | 0.06 | 0.03 | 0.010 |
| 4 | 0.03 | 0.01 | 0.0052 |
| 5 | 0.01 | 0.008 | 0.0019 |
| 6 | 0.008 | 0.005 | 0.00065 |
| 7 | 0.0075 | 0.0048 | 0.00064 |
| 8 | 0.0070 | 0.0048 | 0.00058 |
| 9 | 0.0064 | 0.0043 | 0.00058 |
| 10 | 0.0062 | 0.0035 | 0.00058 |

In this table, the bit error rate calculation for the iteration 10 is measured for the methods such as AntLion, PSO-MSQPA and proposed MLGS-PIM. From the table the bit error rate calculation of MLGS-PIM varies from 0.030 to 0.00058 where for the earlier methods like AntLion and PSO-MSQPA it varies from 0.1 to 0.0062 and 0.07 to 0.0035 respectively. As a result the bit error rate is lower for the

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proposed MLGS-PIM when compared with the earlier researches which are achieved with the help of ML algorithm for the process of optimal parameters selection with gating system.

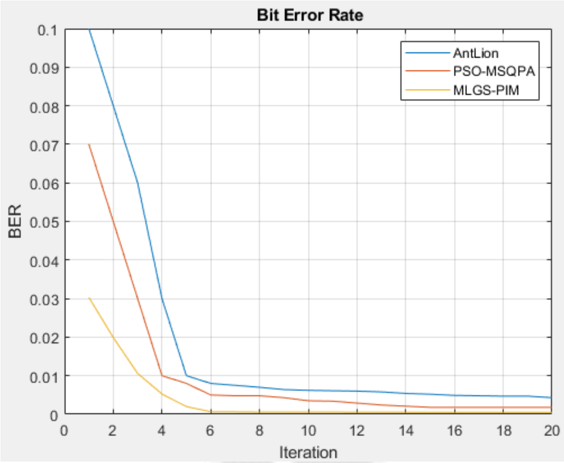


Figure 11 – Bit Error Rate Calculation for Iteration 20

Figure 11 illustrates the calculation of bit error rate for the iteration of 20 counts and the analyses are performed for the methods like AntLion, PSO-MSQPA and proposed MLGS-PIM. Therefore attaining lesser sum rate is the aim to get the successful end results the proposed MLGS-PIM achieved lower bit error rate when compared with the earlier researches in PIM process and it gets attained using the novel machine learning algorithm in the MLGS-PIM for the process of optimal parameter selection. The numerical analysis of the bit error rate calculation for 20 iteration counts are given in table 9.

Table 9 - Bit Error Rate Value Analysis for Iteration 20

| Iteration | AntLion | PSO-MSQPA | MLGS-PIM |
|---|---|---|---|
| 2 | 0.08 | 0.05 | 0.0199 |
| 4 | 0.03 | 0.01 | 0.0052 |
| 6 | 0.008 | 0.005 | 0.00065 |
| 8 | 0.007 | 0.0048 | 0.00058 |
| 10 | 0.0062 | 0.0035 | 0.00058 |
| 12 | 0.0060 | 0.0029 | 0.00054 |
| 14 | 0.0054 | 0.0021 | 0.00053 |
| 16 | 0.0049 | 0.0018 | 0.00049 |
| 18 | 0.0047 | 0.0018 | 0.00049 |
| 20 | 0.0043 | 0.0018 | 0.00049 |

In this table, the bit error rate calculation for the iteration 20 is measured for the methods such as AntLion, PSO-MSQPA and proposed MLGS-PIM. From the table the bit error rate calculation of MLGS-PIM varies from 0.0199 to 0.00049 where for the earlier methods like AntLion and PSO-MSQPA it varies from 0.08 to 0.0043 and 0.05 to 0.0018 respectively. Accordingly the bit error rate is lower for the proposed MLGS-PIM than others with the help of ML algorithm for optimal parameters selection with gating system of 3, 4 and 5 gates.

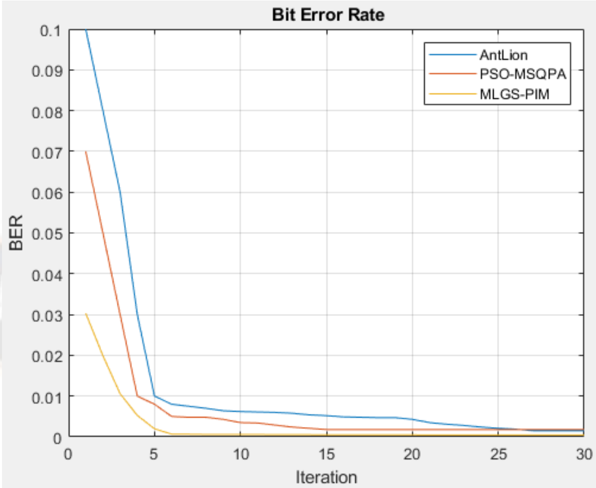


Figure 12 – Bit Error Rate Calculation for Iteration 30

Figure 12 shows the calculation of bit error rate for the iteration of 30 counts and the analyses are performed for the methods like AntLion, PSO-MSQPA and proposed MLGS-PIM. From figure it is confirmed that the proposed MLGS-PIM produced lower bit error sum rate during the PIM process where that helps to achieve effective end results which is achieved using the algorithms like ISVM and ANN. The numerical analysis of the bit error rate calculation for 30 iteration counts are given in table 10.

Table 10 - Bit Error Rate Value Analysis for Iteration 30

| Iteration | AntLion | PSO-MSQPA | MLGS-PIM |
|---|---|---|---|
| 3 | 0.06 | 0.03 | 0.0105 |
| 6 | 0.008 | 0.005 | 0.00065 |
| 9 | 0.0064 | 0.0043 | 0.00058 |
| 12 | 0.0060 | 0.0029 | 0.00054 |
| 15 | 0.0052 | 0.0018 | 0.00049 |
| 18 | 0.0047 | 0.0018 | 0.00049 |
| 21 | 0.0035 | 0.0018 | 0.00047 |
| 24 | 0.0024 | 0.0018 | 0.00046 |
| 27 | 0.0015 | 0.0018 | 0.00046 |
| 30 | 0.0015 | 0.0018 | 0.00046 |

In this table, the bit error rate calculation for the iteration 30 is measured for the methods such as AntLion, PSO-MSQPA and proposed MLGS-PIM. From the table the bit error rate calculation of MLGS-PIM varies from 0.0105 to 0.00046 where for the earlier methods like AntLion and PSO-MSQPA it varies from 0.06 to 0.0015 and 0.03 to 0.0018 respectively. Accordingly the bit error rate is lower for the

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proposed MLGS-PIM than others with the usage of ML algorithms like ISVM and ANN with gating system.

5.3 Convergence Plot Calculations for varying iterations:

In this section the convergence plot of the methods such as AntLion, PSO-MSQPA and proposed MLGS-PIM is calculated for varying iteration such as 10, 20 and 30. Figure 13, 14 and 15 shows the convergence plot of the methods which are involved in this process and it values are analyzed in table 11, 12 and 13.

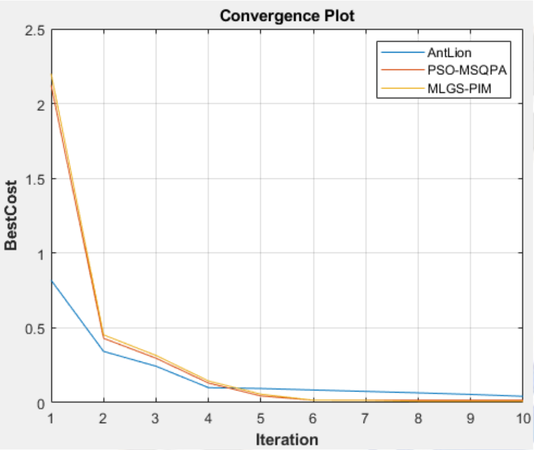


Figure 13 – Convergence Plot Calculation for Iteration 10

Figure 13 demonstrate the calculation of convergence plot for the iteration of 10 counts and the analyses are performed for the methods like AntLion, PSO-MSQPA and proposed MLGS-PIM. To accomplish valuable end product it is vital to increase the convergence. From the performance outcome it is shown that the proposed MLGS-PIM produced higher convergence by the use of effective machine learning algorithm such as improved SVM and ANN for parameters selection. The numerical analysis of the convergence calculation for 10 iteration counts are given in table 11.

Table 11 - Convergence Plot Value Analysis for Iteration 10

| Iteration | AntLion | PSO-MSQPA | MLGS-PIM |
|---|---|---|---|
| 1 | 0.819 | 2.122 | 2.209 |
| 2 | 0.342 | 0.430 | 0.453 |
| 3 | 0.243 | 0.297 | 0.315 |
| 4 | 0.100 | 0.131 | 0.145 |
| 5 | 0.094 | 0.044 | 0.056 |
| 6 | 0.084 | 0.016 | 0.016 |
| 7 | 0.074 | 0.016 | 0.015 |
| 8 | 0.065 | 0.016 | 0.009 |
| 9 | 0.054 | 0.016 | 0.009 |
| 10 | 0.042 | 0.016 | 0.009 |

In this table, the convergence calculation for the iteration 10 is measured for the methods such as AntLion, PSO-MSQPA and proposed MLGS-PIM. From the table the convergence calculation of MLGS-PIM varies from 2.209 to 0.009 where for the earlier methods like AntLion and PSO-MSQPA it varies from 0.819 to 0.042 and 2.122 to 0.016 respectively. Accordingly the convergence is higher for the proposed MLGS-PIM than others with the usage of ML algorithms like ISVM and ANN with gating system.

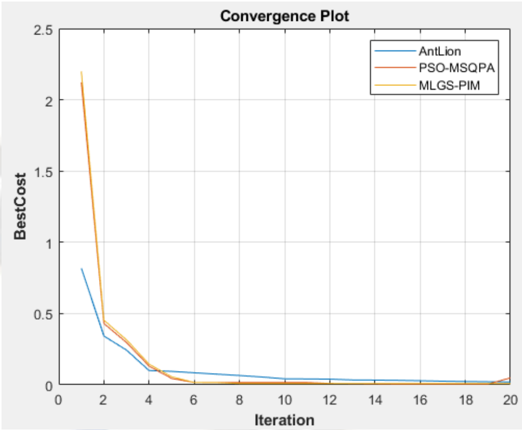


Figure 14 – Convergence Plot Calculation for Iteration 20

Figure 14 illustrates the calculation of convergence for the iteration of 20 counts and the analyses are performed for the methods like AntLion, PSO-MSQPA and proposed MLGS-PIM. Hence reaching higher convergence is the objective to acquire effective end results the proposed MLGS-PIM produced maximum convergence when compared with the earlier researches in PIM and it becomes possible using the innovative machine learning algorithm in the MLGS-PIM process. The numerical analysis of the convergence calculation for 20 iteration counts is given in table 12.

Table 12 - Convergence Plot Value Analysis for Iteration 20

| Iteration | AntLion | PSO-MSQPA | MLGS-PIM |
|---|---|---|---|
| 2 | 0.34 | 0.43 | 0.45 |
| 4 | 0.10 | 0.13 | 0.14 |
| 6 | 0.08 | 0.016 | 0.016 |
| 8 | 0.065 | 0.016 | 0.0094 |
| 10 | 0.042 | 0.016 | 0.0094 |
| 12 | 0.039 | 0.0098 | 0.0094 |
| 14 | 0.033 | 0.0071 | 0.0094 |
| 16 | 0.028 | 0.0054 | 0.0094 |
| 18 | 0.023 | 0.0052 | 0.0094 |
| 20 | 0.020 | 0.048 | 0.0094 |

In this table, the convergence calculation for the iteration 20 is measured for the methods such as AntLion, PSO-MSQPA and proposed MLGS-PIM. From the table the convergence calculation of MLGS-PIM varies from 0.45 to 0.0094 where for the earlier methods like AntLion and PSO-MSQPA it

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varies from 0.34 to 0.020 and 0.43 to 0.048 respectively. Accordingly the convergence is higher for the proposed MLGS-PIM than others in this research which is achieved using the ML algorithms.

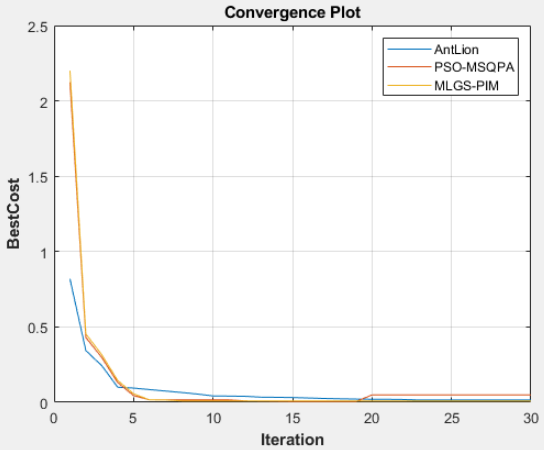


Figure 15 – Convergence Plot Calculation for Iteration 30

Figure 15 shows the calculation of convergence for the iteration of 30 counts and the analyses are performed for the methods like AntLion, PSO-MSQPA and proposed MLGS-PIM. From figure it is proven that the proposed MLGS-PIM produced high convergence during the process of PIM where that helps to achieve better results which is achieved using the algorithms like ISVM and ANN. The numerical analysis of the convergence plot calculation for 30 iteration counts are given in table 13.

Table 13 - Convergence Plot Value Analysis for Iteration 30

| Iteration | AntLion | PSO-MSQPA | MLGS-PIM |
|---|---|---|---|
| 3 | 0.24 | 0.29 | 0.315 |
| 6 | 0.08 | 0.016 | 0.016 |
| 9 | 0.054 | 0.016 | 0.0094 |
| 12 | 0.039 | 0.0098 | 0.0094 |
| 15 | 0.031 | 0.00541 | 0.0094 |
| 18 | 0.0231 | 0.00521 | 0.0094 |
| 21 | 0.0198 | 0.04897 | 0.0094 |
| 24 | 0.0151 | 0.04897 | 0.0094 |
| 27 | 0.0151 | 0.04897 | 0.0094 |
| 30 | 0.0151 | 0.04897 | 0.0094 |

In this table, the convergence calculation for the iteration 30 is measured for the methods such as AntLion, PSO-MSQPA and proposed MLGS-PIM. From the table the convergence calculation of MLGS-PIM varies from 0.315 to 0.0094 where for the earlier methods like AntLion and PSO-MSQPA it varies from 0.24 to 0.0151 and 0.29 to 0.048 respectively. Accordingly the convergence is higher for the proposed MLGS-PIM than others in this research which is achieved using the machine learning algorithms and gating systems.

## VI. Conclusion:

In this research work, the Plastic Injection Molding (PIM) based process parameters are optimized to achieve effective end results with the help of the machine learning algorithm like ISVM and ANN. The major parameters which are considered for that parameters description are injection time, mold temperature, melt temperature, packing pressure, process efficiency and process reliability. These are the experimentation factors for the simulation process in the PIM machine. With the help of these parameters the simulation is designed and completed. The PIM process parameters of the optimized based on the machine learning algorithm such as ISVM and ANN models. The results are evaluated for three materials namely thermoplastic polystyrene, thermoplastic acrylonitrile butadiene styrene and thermoplastic polyvinyl chloride where three types are gating systems are applied with it and consists of 3, 4 and 5 gates. During the simulation of the PIM process with the help of optimal parameter selection and gating system the effective volume shrinkage is achieved and as well the parameters which are measured for the output analysis are sum rate, bit error rate and convergence plot. The results show that the outcome of the proposed MLGS-PIM considerably increases the performance when compared with the earlier approaches like AntLion Optimization and PSO-MSQPA. In the future direction, for the process of further improvement energy dissipation is concentrated.

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