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A Comprehensive Review of the Use of Integrated Approaches for Parameter Optimization and Defect Reduction in Foundries

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Abstract

Casting is a versatile, cost-efficient manufacturing process for parts with no shape and size constraints. Although a range of metals and their alloys may be easy to work with, process design and control are complex. Foundries struggle a lot with defects and yield of castings, losing crucial time in trial-and-error experimentation or following their own thumb rules of development despite the product complexities. This review will shed light on the use of combined techniques like integration of the Taguchi method with numerical simulation, grey relational analysis (GRA), artificial neural network (ANN), and genetic algorithm (GA). This paper also includes combined methods that include Response Surface Methodology (RSM), Numerical Simulation, Artificial Fish-Swarm Algorithm (AFSA), Particle Swarm Optimization (PSO), Weighted Aggregated Sum Product Assessment (WASPAS), Material Generation Algorithm (MGA), Sunflower Optimization, Ant Lion Algorithm for multiobjective optimization, and defect reduction in majorly used casting processes.

Keywords: Casting Defects, Combined Techniques for Defect Reduction, Defect Reduction, Parameter Optimization

1- Introduction

The major success of all casting processes depends upon close control over all the input parameters and metal solidification. Due to the involvement of advanced technologies in the casting process, a variation in any of the input parameters affects the process output and produces defective castings. However, the designers and foundry personnel are making great efforts to develop various mathematical models of input-output relations to achieve exact parameter settings instead of trial and error. Determining the optimal process parameters influences product quality and costs. Table 1 shows key Process Parameters in Major Casting Processes as developed from a variety of online articles.

Standard practices of designing parts, developing tooling development, process parameter selections, quality checks, and standards are getting adopted by modern-day foundries. Also, sustainability has raised growing concerns over rework and rejections, which only be done by numerous virtual trials, active process control through parameters, and process improvements. Optimization of process parameters and gating system design can solve many of the above problems. Most casting defects are due to improper gating and feeding system designs/ configurations. Table 2 shows a summary of commonly observed defects and their categorization. Combined Techniques can help various process parameters optimization, gating, and feeding systems design with sustainable practices to get sound castings.

Table 1- Process Parameters in Major Casting Processes

Sr. No.	Name of the Casting Process	Process Parameters
1	Sand Casting	Moisture, Sand Particle Size, Green Compression Strength, Mould Hardness, Permeability, Pouring Temperature, Pouring Time, Cooling Time, etc.
2	Gravity Die Casting	Pouring Velocity, Melt Holding Time, Pouring Time, Mould Temperature at The Time of Pouring, Gate and Riser Design, Degasification, Preheat Temperature, Die Coat Material, and its Thickness, etc.
3	Pressure Die Casting	Injection pressure, the molten metal temperature, the plunger velocity (first and second stage), Die Temperature, Piston, Die Gate Velocity, Solidification Pressure, etc.
4	Investment Casting	Wax Composition, Surry Composition, Preheat Temperature, Pouring Time, Pouring Temperature, Die Temperature, Cooling Time, etc.
5	Shell Molding	Shell Material Composition, Shell Coating, Pre Heating Temperature, Pouring Temperature and Rate, Cooling Time and Method, Shakeout and Cleaning Techniques, Core Design and Placement, Mold Venting, etc
6	Injection Moulding	Barrel Temperature, Injection Speed, Injection Time/Volume, Injection Speed, Injection/Holding Pressure, Packing/Holding Time, Cooling Time, Open Mould Time, Mould Temperature, Melt Temperature, Melt Viscosity, Filling Time, Filling Pressure, Screw Rotation Speed, etc.

Table 2- Commonly Observed Defects

Sr. No.	Defects Category	Defects
1	Gas Porosity	Pin Holes, Subsurface Blow Holes, Open Holes, Shrinkage Porosity, Gas Inclusion
2	Shrinkage	Open and Close Shrinkage Defects
3	Mould	Cuts and Washes, Fusion, Run Out, Swell, Drops, Rattail, Veins and Buckles, Metal Penetration, Mold Shift, Mold Erosion
4	Pouring Metal	Cold Shut/ Lap, Misruns, Cold Shots, Slag Inclusion (Scab)
5	Metallurgical	Hot Tear/Crack, Hot/ Hard Spots
6	Casting Shape Defects	Shift/ Mismatch, Flash, Fin, and Burrs, Warping

The use of Taguchi, ANOVA GA, RSM, Numerical Simulation, Back Propagation Neural Network, GRA (Gray Relational Analysis),AFSA, PSO, WASPAS, MGA, Sunflower Optimization, Ant Lion Algorithm has enhanced the process of optimization and helped to reduce the defects in foundries when integrated overcoming major issues of use of single technique, Casting simulations are widely practiced in foundries to fine-tune Productivity, Quality, Cost, Delivery, Safety, and Morale, regardless of the foundry size. It is known that BP neural network [1] has the powerful ability of nonlinear interpolation to obtain the mathematical mapping reflecting the internal law of the experimental data. Therefore, BP neural network has been widely used in engineering applications for prediction and optimization [2–4]. GRA (Gray Relational Analysis) which was first suggested by Deng in 1989[5] is often coupled with Taguchi by various researchers. For multifactor optimization problems, combining RSM as described [6,7] with AFSA as used in [89] can be effectively integrated. The PSO algorithm is a global optimization algorithm and is described as sociologically inspired as illustrated in [10] is routinely clubbed with ANN and Taguchi.

In recent years, one of the most prominent multi-criteria decision-making approaches has been the WASPAS technique [11–16]. It is an aggregate of two simple approaches namely weighted sum method along with weighted product method. This Taguchi-WASPAS pair of optimization techniques is found superior for many multiobjective optimization problems. As formulated by Siamak Talatahari, Mahdi Azizi, and Amir H. Gandomi in the year 2021 [17–19], Material Generation Algorithm is a bio-inspired algorithm particularly derived from material chemistry has the potential to get clubbed with many of the optimization techniques. Seyedali Mirjalili presented the Ant Lion Optimizer (ALO), a novel nature-inspired algorithm that he called the Ant Lion Optimizer (ALO) [20,21]. The ALO is designed to mimic the natural hunting method used by ant lions and is used in many works with Taguchi-WASPAS for better results. A sunflower's life cycle is consistent: like the needles of a clock, they arise every day. They go in the other way at night to await their disappearance the following morning [22,23]. This has led to the generation of a sunflower optimization algorithm which is successfully combined with the Taguchi method for defect reduction.

The contribution of this work is to showcase how these methods are to be used for process parameter optimization and defect reduction with the description of carried out work for various casting processes. In the end, a summary of the literature reviewed in a tabular format (Table 3) highlighting the authors, techniques combined, objectives of optimization, and parameters considered in this process is presented.

2-Defect Analysis and Reduction by Combining Different Techniques

Reference [24] proposed a new classification methodology based on the effect of defects on casting into geometry, integrity, and property-related defects. This 3-step approach used for defect identification, analysis, and rectification classifies the casting defects in terms of their appearance, size, location, consistency, discovery stage, and inspection method for correct identification of the defects. Then possible causes are grouped into design, material, and process parameters. A new hybrid approach combines Numerical Simulation and Artificial Neural Networks (ANN) after preparing the Design of Experiments (DOE). The simulation determines the effect of suspected cause parameters on casting quality. As per the results and their interpretation, the optimal values of the parameters are determined to eliminate the defects.[24]

Article [25] combined two techniques of design experiments and computer-assisted casting simulation techniques to analyze the defects in green sand casting. The casting defects observed were categorized into two major categories. The first is for sand and mold-related defects like sand drops, poor mold, blowholes, cuts, and washes. Taguchi method was used for optimum casting process parameters selection with the objective of minimum rejection and maximum yield due to defects in a new casting or defect analysis in existing castings. The second category includes methods, filling, and solidification-related defects such as shrinkage porosity and hot tears addressed through iterative computer simulations.[25]

Reference [26] used a combined artificial neural network and particle swarm optimization (PSO) algorithm to optimize the injection moulding process. Within the considered example of the PC vehicle window under Impact Loading, optimum values of process parameters are determined to minimize the maximum von Mises stress within the. An integrated finite element analysis of the injection moulding process, the warpage-induced residual stresses during assembly, and the mechanical performance of the serviced product are first proposed. Later a back propagation neural network model is developed to map the complex nonlinear relationship between process parameters and the mechanical performance of the product. Mechanical performance improvement is by interfacing the PSO algorithm with this predictive model to optimize process parameters.[26]

The work of [27] presents a detailed analysis of the vacuum casting (VC) process and the intricate mould-filling mechanism for Warpage reduction. A mathematical model for the filling process using fluid dynamics relationships is formulated and is followed by its simulation using a numerical simulation algorithm. A novel warpage strategy integrating the response surface methodology (RSM) and the artificial fish-swarm algorithm (AFSA) is used for optimization. The RSM plays a crucial role in establishing the correlation between process parameters and warpage, while the ASFA is employed to determine the optimized process parameters. Both simulations and experiments conducted validate the accuracy of the model and the reliability of the algorithm. Ultimately, the results affirm that this optimization approach significantly reduces warpage in VC parts and improves product quality. Therefore, this cost-effective method stands as a dependable solution for optimizing process parameters in Vacuum Casting technology.[27]

In this study [28], a novel approach combining an artificial neural network and particle swarm optimization (PSO) algorithm is presented for the optimization of the injection moulding process. The research introduces an integrated finite element analysis that considers the injection moulding process, the residual stresses induced by warpage during assembly, and the mechanical performance of the final product. To capture the intricate nonlinear relationship between process parameters and product performance, a back propagation neural network model is developed. The PSO algorithm is then employed, interfacing with the predictive model to optimize the process parameters. Through this combined approach, a substantial enhancement in the mechanical performance of the product can be achieved. [28]

The paper [29] demonstrated the effective use of genetic algorithm and numerical simulation for optimizing the gating system of an excavator tooth holder in sand casting. The GA was used to optimize the gating system to maximize the filling rate while considering constraints imposed by the ingate module and Reynolds number. The relationship between mould filling time, ingate cross-section, and casting height was analyzed and presented. By applying the GA optimization process, the gating system geometry is determined and further validated using the numerical simulation by MAGMA5 software. The results of the simulation confirmed the geometry optimization and ensured its effectiveness in achieving the desired casting properties.[29]

Reference [30] identified and optimized various significant process parameters of high-pressure die casting by using Quality Function Deployment (QFD-Taguchi based hybrid approach to yield the optimum casting density of the A380 alloy. To study the performance characteristic of the die-casting process the finding of critical process parameters, selection of appropriate orthogonal array, analysis of means, and Analysis of Variance (ANOVA) are used. The most critical process parameters identified and optimized using the QFD-Taguchi based hybrid approach are the injection pressure, the molten metal temperature, the plunger velocity (first and second stage), and the die temperature.[30]

The study of [31] identifies the effect of moulding parameters on defects such as weld line and sink mark. The experiments were performed using L27 Orthogonal Array and normalized by Grey relational analysis (GRA). The input variables were considered by using ANOVA. To determine optimal moulding parameters Taguchi method constructed GRA was used.[31]

In the work of [32], the Six Sigma DMAIC approach was successfully used in identifying the problem, improving the process, and controlling the defects. Six Sigma DMAIC methodology was used to identify the problems in a casting process and solve the problem by determining the optimal operation parameters for reducing blow hole and sand inclusion defect. The problem was refined in the define phase to create a viable project. The current condition of the company was checked in the measure phase and significant parameters were identified in the analysis phase. In the improvement phase, the Taguchi method was applied to the set of process parameters. In the control phase, the optimal parameter setting for reducing the blow hole and sand inclusion defects was done. The effect of casting parameters on the casting defect was evaluated, with the help of Taguchi analysis, and optimal casting parameter conditions were determined to minimize the percentage of defects. ANOVA was used to find out that the mould hardness and pouring rate are more significant out of selected parameters moisture content, permeability, mould hardness, green strength, pouring temperature, and pouring rate.[32]

Researchers in [33] developed and showcased a procedure to optimize product quality in terms of strength and micro-structure and process productivity in terms of solidification time by obtaining optimal initial and wall temperatures. Non-dominated sorting genetic algorithm (NSGA-II) was used for multi-objective optimization of the solidification process during die casting. However, due to the extensive number of function evaluations required by NSGA-II, direct utilization of the finite volume solver for optimization was not feasible. As a solution, they trained a multilayer perceptron feed-forward neural network using the numerical results of fluid flow and energy equations to serve as a surrogate model. To validate the results of the genetic algorithm, simplified versions of the problem were utilized. In addition to this, an innovative local sensitivity-based approach was employed to rank the final Pareto optimal solutions and identify the most optimal design.[33]

Artificial Neural Network (ANN) algorithms were employed to predict casting defects such as shrinkage and micro-porosity by Reference [34]. To achieve this, a series of simulation-experimental tests were conducted to gather data on cooling rate, solidification time, temperature, liquid phase, initial mould temperature, and %shrinkage. The results obtained from the ANN modeling exhibited a strong correlation with the experimental data, demonstrating the effectiveness of the approach.[34]

Reference [35]worked with the properties of green sand used in moulding which can be influenced by the sand composition, with key parameters including green strength, moisture content, and clay content. In this study, different compositions of silica oxide were blended with green sand for the cope box. Experimental investigations were carried out using Response Surface Methodology (RSM) to analyze the various sand parameter compositions. The results of the sand parameters were compared with an analysis using Artificial Neural Network (ANN). The findings revealed that by blending SiO_2 with green sand, the initial raw material volume could be reduced by up to 25% without causing casting defects.[35]

The primary objective of this study [36] was to simulate the high-pressure die casting of A356 semi-solid aluminum alloy using a casting process simulation tool. The focus was on considering the viscosity of the semi-solid slurry and the mould-filling behaviour in high-pressure die casting. To achieve this, a specially designed mould for the semi-solid aluminium alloy was developed. The study also aimed to investigate the effects of three input parameters, namely the liquid fraction of the slurry, plunger velocity during the second phase, and mould geometry, on various aspects of the semi-solid high-pressure die casting process, such as casting time, shrinkage, and bubble formation. To determine the optimal process parameters, the Taguchi-based grey relational analysis approach was employed. Additionally, the analysis of variance (ANOVA) technique was used to assess the significance of each controllable parameter on the performance characteristics [36]

In reference [37] an experimental study was conducted to investigate the impact of sand grain size, curing time, and binder on the compression strength, core hardness, and shear strength of chemically bonded no-bake sand mould cores. To optimize the control parameters, a hybrid statistical and meta-heuristic optimization approach was employed, specifically the Taguchi-based WASPAS method and Material Generation algorithm. The predicted values obtained through this approach closely matched the experimental values obtained from confirmatory tests, indicating the effectiveness of the optimization methodology. [37]

An experimental study was conducted in reference [38] to assess the impact of catalyst percentage, grain size, and the number of compression strokes on the collapsibility and core shrinkage of chemically bonded no-bake sand mould cores. The control parameters were optimized using two different approaches: the statistical Taguchi technique and the nature-inspired meta-heuristic Sunflower optimization algorithm. The results obtained through the Sunflower optimization algorithm closely matched the experimental values obtained from confirmatory tests, indicating its superior precision compared to the Taguchi technique. [38]

The investigation of [39] focused on the transparent top sheath used in male/female deodorants and aimed to minimize weld-line width and sink-mark depth during the injection molding process of commercial-grade transparent thermoplastic (Polymethyl Methacrylate). Eight plastic injection molding criteria were considered: melting temperature, mold temperature, cooling time, injection pressure, back pressure, holding pressure, ambient temperature, and holding time. To optimize these factors, Taguchi's Design was employed, conducting 27 experiments. The Taguchi-based WASPAS method (Weighted Aggregated Sum Product Assessment), the Ant Lion optimization algorithm, and analysis of variance were utilized to determine the most influential parameter in minimizing the weld-line width and sink mark depth of the plastic injection molded part.[39]

3-Summary of Reviewed Articles

Table 3- Consolidated Summary of the Use of Combined Techniques in Parameter Optimization and Defect Reduction for Various Casting Processes

Sr. No.	Name of the Authors	Combined Techniques Used for Optimization and Defect Reduction	Objectives of the Study	Process Parameters Considered
1	V.V. Mane et al. (2011) [24]	Design of Experiments (Taguchi)+ Numerical Simulation +Artificial Neural Networks (ANN)	Defect Reduction	For Defect Analysis, Parameters are Grouped into Design, Material, and Process Parameters
2	Uday A. Dabade and Rahul C. Bhedasgaonkar (2013) [25]	Taguchi+Analysis of Variance (ANOVA)+Numerical Simulation	Optimization of Process Parameters Associated with Moulding Sand for Defect Reduction	Moisture Content (%), Green Compression Strength, Permeability of Moulding Sand And Mould Hardness (In the Horizontal Direction)

3	Yingjie Xu et al. (2015) [26]	Response Surface Methodology(RSM)+Artificial Fish-Swarm Algorithm (AFSA)	Numerical Simulation of Filling Process, Warpage Reduction by Optimization of Process Parameters	Pressure Difference and Temperatures of the Material and Mould
4	H. G. Zhang et al. (2016)[27]	Numerical Simulation + Artificial Neural Network +Particle Swarm Optimization (PSO)	Optimization of Injection Molding Process Parameters to Improve the Mechanical Performance of Polymer Products Against Impact	Mold Temperature (°C) Melt Temperature (°C) Injection Velocity (Cm3/S) Compression Distance (Mm) Compression Force (T), Compression Velocity (Cm/S), Compression Waiting Time (S)
5	Xue-dan Gong et al. (2016)[28]	Artificial Neural Network +Genetic Algorithm (GA)	Optimization of Steel Casting Feeding System for Shrinkage Cavity or Porosity Defects	Riser Type, Riser Cross-Sectional Area, Riser Height, Chill, and Pouring Temperature
6	Nedeljko Dučić et al. (2016)[29]	Genetic Algorithm + Numerical Simulation	Geometry Optimization of the Gating System of Sand Casting	Ingate Cross-Section Area, Height Between the Bottom Surface of the Casting Part and the Level of Molten Metal and a Basin
7	K. Ch. APPARAO et al. (2017)[30]	Taguchi+ Quality Function Deployment (QFD)	Optimization of Process Parameters of High Pressure Die Casting for Optimum Casting Density	1) Parameters Related to Die Casting Machine: Plunger Velocity During First and Second Stage, Fast Shot Set Point, Cavity Filling Time, Multiple Pressures During 3rd Stage. 2) Parameters Related to Shot

				Sleeve: Dimensions and Filling Time of Shot Sleeve. 3) Type of Die Lubricant. 4) Parameters Related to the Die: Temperature of the Die, Size and Shape of the Gate, the Venting System of Die Design, the Cooling System of Die Design. 5) Parameters Related to Cast Metal: Temperature of the Casting Metal, Condition, and Composition of the Cast Metal.
8	Sreedharan J. et al. (2018) [31]	Taguchi+Grey Relational Analysis (GRA)	Optimization of Moulding Parameters for Defects like Weld Line and Sink Mark.	Mold Temperature (°C) Melt Temperature (°C) Injection Pressure (MPa) Holding Pressure (MPa) Cooling Time (Sec) Back Pressure (MPa) Holding Time (Sec) Ambient Temperature (°C)
9	M. M. Ganganallimath et al. (2019) [32]	Taguchi+Six Sigma	Optimization of Process Parameters for Defect Reduction, Improving the Six Sigma Value of the Company	Mould Hardness, Moisture Content, Green Strength, the Permeability of Sand, Pouring Rate, and Pouring Temperature
10	Shantanu Sahane et al. (2020) [33]	Numerical Simulation+Machine Learning	Minimization of Solidification Time, Yield Strength, and Maximization of Grain Size	Initial and Wall Temperatures

11	L.C. Kumruoglu et al. (2021) [34]	Artificial Neural Network +Numerical Simulation	Reduction of Shrinkage and Micro-Porosity Defects	Initial Mould Temperature, Pouring Time, Casting Temperature, Cooling Rate, And % Critical Liquid Phase
12	G. Mahesh et al. (2021) [35]	Response Surface Methodology(RSM)+ Artificial Neural Network	Optimization of Aluminum Sand Casting Process Parameters for Reducing Surface Roughness and Increasing the Hardness	Moisture Content%, Clay Content %, Silica Oxide (Sio2) %
13	Ivana Dumanic et al. (2021) [36]	Taguchi+Numerical Simulation+ANOVA+Gery Relational Analysis	Porosity, Shrinkage and Cycle Time Reduction	Liquid Fraction (%), Second Phase Velocity (m/s), Mold Geometry (Configuration), Total Casting Time (s), Shrinkage (%,) Bubble Formation (%)
14	Nirmal Chandra Behera et al. (2021) [37]	Taguchi+ ANOVA+Weighted Aggregated Sum Product Assessment (WASPAS)	Parameter Optimization for Fabrication of No-Bake Chemically Bonded Sand Mould Core with Maximization of Compressive Strength, Shear Strength, and Core Hardness	Size Of Sand Grains (GFN), Binders (Wt. % of Sand), Curing Time (Hr)
15	Soubhagya Malik et al. (2021) [38]	Taguchi+Sunflower Optimization	Parameter Optimization for maximize Collapsibility and Minimize Core Shrinkage	Catalyst (ml), No. of Strokes, Grain Fineness Number
16	Bammidi Ravikiran et al. (2021) [39]	Taguchi+ Weighted Aggregated Sum Product Assessment (WASPAS)+Ant Lion Optimization	Minimization of Weld-Line Width and Sink Mark Depth of the	Melting Temperature, Mould Temperature, Cooling Time, Injection Pressure, Back Pressure, Holding Pressure, Ambient Temperature, and

		Algorithm+ANOVA	Plastic Injection Moulded Part	Holding Time.

4- Current Ongoing and Future Research Areas in Casting

Current ongoing and future research areas in casting focus on improving process efficiency, enhancing product quality, and exploring new materials and technologies. The field continues to evolve with advancements in materials, technologies, and process optimization, leading to improved casting quality, reduced costs, and enhanced sustainability. Some of the compiled current and future research areas in casting as per the reviewed literature, technical articles available on the web, and interaction with foundry workers, supervisors, managers etc. in Aurangabad (Maharashtra, India) region are as:

1- Advanced Materials: Research is being conducted to develop new alloys and composite materials that offer improved mechanical properties, such as strength, durability, and heat resistance. These materials can enhance the performance of cast components in various industries. The utilization of nonferrous alloys like zinc, copper, aluminum, magnesium, lead, pewter, and tin-based alloys is increasingly becoming a prominent trend. While steel has traditionally been widely employed in various applications due to its strength and low weight, there is a growing interest in substituting it with lighter alternatives such as aluminum, magnesium, and zinc. These materials do possess good strength and are lower in weight, making them suitable for a range of applications. Additionally, brass stands out as an exceptional example of casting in automotive and consumer electronics industries, primarily due to its remarkable corrosion resistance and unparalleled conductivity properties.

2- Process Optimization: Ongoing research aims to optimize casting processes by improving mold design, gating systems, and process parameters. Computer simulations and modeling techniques are utilized to optimize filling and solidification processes, reduce defects, and enhance the overall casting quality.

3- Additive Manufacturing and 3D Printing: Casting is being combined with additive manufacturing techniques to create intricate molds and cores, which were previously difficult to produce. This approach allows for the production of complex geometries and customized cast components with reduced lead times.

4- Surface Treatment and Finishing: Research is focused on developing innovative surface treatment and finishing techniques to enhance the appearance, corrosion resistance, and wear resistance of cast components. Surface modifications like coatings shot peening, and laser treatments are being investigated to improve the performance and longevity of cast products.

5- Solidification Modeling: Solidification behavior plays a crucial role in determining the microstructure and mechanical properties of castings. Researchers are working on improving solidification models to predict and control defects like porosity, shrinkage, and segregation, thereby optimizing the casting process.

6- Sustainable Casting: With a growing emphasis on sustainability and environmental impact reduction, research is being conducted to develop eco-friendly casting processes. This includes exploring alternative mold materials, energy-efficient melting techniques, and recycling and reusing casting materials. Energy mapping and optimization can also be explored by researchers.

7- Casting Defect Analysis and Prevention: Research is aimed at understanding and mitigating casting defects, such as porosity, shrinkage, and cracks. Advanced inspection techniques, non-destructive testing methods, and process monitoring systems are being developed to detect and prevent defects early in the casting process. The development of robust yet simple methods for defect analysis and prevention which can be routinely used by shop floor personnel can be an area of research. Intelligent Inspection systems which incorporate image processing, machine learning, and artificial intelligence, have the potential to provide more accurate and efficient inspection results. Researchers can work on developing such inspection devices.

8- Robotics and Automation: Automation in casting processes is being explored to improve productivity, reduce labor costs, and enhance workplace safety. Robotic systems are being developed for tasks like mold preparation, pouring, and post-casting operations.

9- Digitalization and Industry 4.0: The integration of digital technologies, such as artificial intelligence, big data, machine learning, and the Internet of Things (IoT), is transforming the casting industry. Research focuses on utilizing real-time data, predictive analytics, and digital twins to optimize process control, minimize downtime, and enable intelligent decision-making. Data analysis is another innovative process that can help metal casting companies to get accurate and dependable information. This can be about the overall productivity, errors, as well as process times.

5- Conclusion

A Conclusive Summary derived from the reviewed work is as follows:

1- The integration of various optimization techniques, such as Taguchi, ANOVA, GA (Genetic Algorithm), RSM (Response Surface Methodology), Numerical Simulation, Back Propagation Neural Network, GRA (Gray Relational Analysis), AFSA (Artificial Fish Swarm Algorithm), PSO (Particle Swarm Optimization), WASPAS (Weighted Aggregated Sum Product Assessment), MGA (Multi-Objective Genetic Algorithm), Sunflower Optimization, and Ant Lion Algorithm, has significantly improved the optimization process and played a vital role in minimizing defects in foundries. This integrated approach effectively overcomes the limitations associated with relying on a single technique.

2- The Taguchi method is utilized to achieve robust design optimization, enabling the identification of optimal process parameters that are less susceptible to variations. ANOVA (Analysis of Variance) can be used to determine the significance of parameters or factors in a statistical model. It is commonly applied in experimental design and analysis to assess the impact of different factors on a response variable. Genetic Algorithms are used for optimization and search problems. They are inspired by the process of natural selection and evolution. ANOVAGA combines analysis of variance (ANOVA) and genetic algorithms to efficiently search for optimal solutions. RSM aids in constructing mathematical models that approximate the behaviour of complex systems and facilitates the optimization of process variables.

3- Numerical simulation techniques enable virtual testing and optimization of designs, reducing the need for physical prototypes and minimizing defects in the foundry process. Back Propagation Neural Networks are employed for pattern recognition, data analysis, and optimization in various stages of the foundry process.

4- GRA provides a systematic approach for evaluating multiple conflicting objectives and helps determine the best compromise solution. AFSA and PSO are population-based algorithms that simulate the behaviour of fish schools and bird flocks, respectively, facilitating efficient search and optimization of solutions.

5- WASPAS is a decision-making method that aggregates criteria weights and evaluates alternatives based on their weighted scores, aiding in the selection of optimal solutions. MGA allows for the simultaneous optimization of multiple conflicting objectives in a foundry process.

6- Sunflower Optimization is a nature-inspired algorithm that mimics the pattern of sunflower seeds to efficiently search for optimal solutions. The Ant Lion Algorithm is another nature-inspired optimization technique that mimics the behaviour of ant lions and has proven effective in solving complex optimization problems.

7- By integrating these techniques, a comprehensive and systematic approach to optimization is achieved, effectively addressing the limitations and challenges associated with individual methods. This integration significantly reduces defects in foundries, leading to improved process efficiency and higher product quality.

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