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Research Article

Review of Computational Approaches used for Investment Casting Process

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ABSTRACT

Investment Casting (IC) is a manufacturing process used to manufacture products with superior surface finish, intricate shapes with tight tolerance for dimension of final product. In IC, wax pattern is dipped into ceramic slurry number of times to develop ceramic shell mold in which molten metal is poured. This paper deals with review of computational approaches carried out for IC. Computational approaches have a vital role in modernizing casting industry by eliminating the traditional methods. Computational approaches such as statistical methods, numerical simulations, and machine learning (ML) are explored in-depth, with case studies focusing on IC applications.

IC has been divided in 3 major stages: 1) Pre-filling stage; includes sub-processes like a) wax pattern making focusing on calculation of shrinkage factor. b) Ceramic coating followed by dewaxing to create ceramic shell mold. 2) Filling is the nest stage of IC where liquid metal is filled into ceramic shell mold; further divided into a) effects of casting process parameters like fluidity, filling manner top or bottom, pouring temperature etc. b) Design of gating system which plays the major role for obtaining defect free casting using. 3) Post filling stage includes knock out & inspection of defect free casting and desired mechanical properties.

Keywords: Investment Casting, Machine Learning, Numerical Simulation, Statiscal Methods.

INTRODUCTION

1.1 Overview of Investment Casting:

IC is the casting process used for 3500 years to develop metal components with superior surface finish having complex and intricate shapes with tight tolerances. Due to high repeatability of producing parts IC is also termed as near net shape producing process (Najafi et al., 2011) . The sequence for IC is classified as pre-filling stage, filling stage & post filling stage (Aguilar et al., 2011)as shown in Fig. 5 IC is used for manufacturing of complex metallic parts which are difficult to manufacture by other processes (P. H. Huang et al., 2020). Domain of IC has reached the fields of medical, defense, aviation, automobile industries and many more with products as dental crowns, gears, jewelry products, turbine blades etc. as they require thin wall castings particularly manufactured by alloys of Titanium, Aluminum and particle reinforced aluminum matrix composites (PR-AlMCs) (Castellanos et al., 2017; Previtali et al., 2008).

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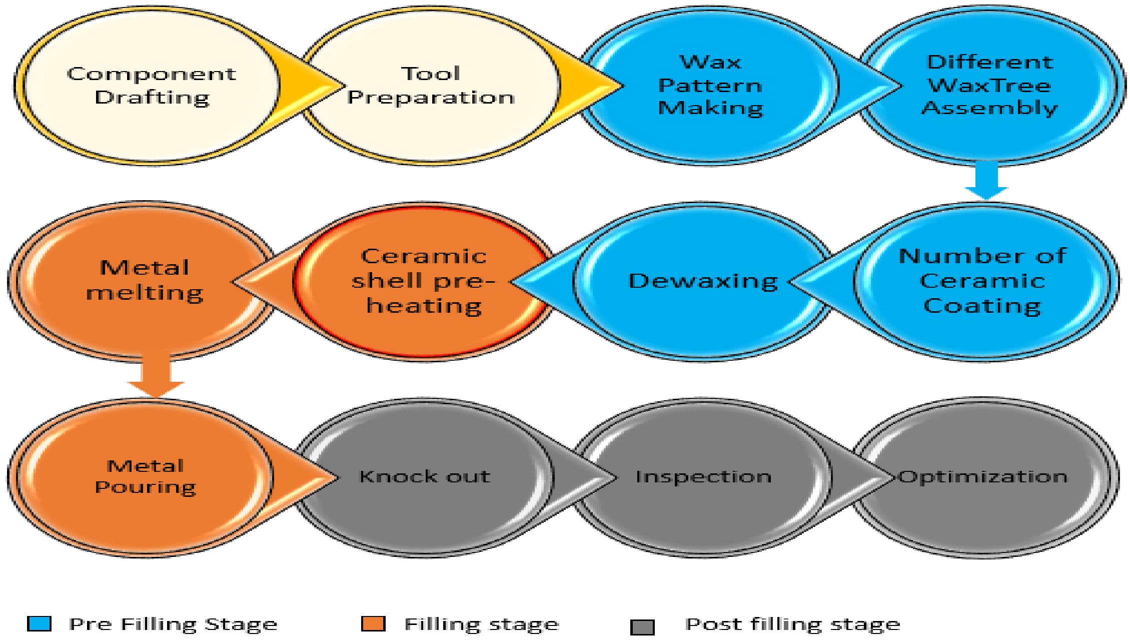

Figure 1 Overview of Investment Casting and its classification

IC has got advantages but has the limitations too; it is time consuming, expensive involving number of processes affecting the final output. Once the drawing of the component is confirmed the next step is developing tool which is time consuming resulting in longer production cycle and also involves sufficient amount of cost. The time duration for the final product delivery ranges from 10 to 25 weeks depending upon the complexity of geometry(Vaghela et al., 2023)**.** Additive manufacturing is trying to replace traditional tooling method to reduce lead times for tool production(Olkhovik et al., 2016) but its impact on environment are checked by sustainability parameters for implementation at industrial level.(Vaghela et al., 2024). Additive manufacturing assisted bio-medical implants had the benefits of a thin wax coating on plastic patterns to reduce surface roughness and prevent shell cracking, with further research needed on wax thickness and pattern allowances for dimensional accuracy(P. Kumar et al., 2016; S. Singh, 2017).

One of the reasons for IC being expensive process is; large number of laborers engaged and high energy consumption. To reduce the labor dependency and cost related to wax room; where 30 % of labor is utilized automation may be implemented(Puffer, n.d.). If cast product doesn't meet the standard of the quality which includes dimensional accuracy, mechanical properties and surface finish. It is to be re-melted; which is undesired and is considered as scrap. The scrap cost contributes around 20 % share in expenditure(Foggia & Addona, 2013) and melting process accounts for around 30-50 % of total energy(Mahrabi et al., 2016). The need of industry is to achieve cost effective non-defective casting with the desired mechanical properties; but as it involves number of sub-processes parameters it is challenging to achieve defect free casting(Venkata Rao & Rai, 2017). Hence different computational approaches like numerical simulation, statistical techniques like Bayesian Inference, the Taguchi Method, Response Surface Methodology (RSM), and ML are employed to address these complexities and improve casting outcomes.(Mane et al., 2011).

1.2 Application of Computational Techniques in Casting

Conventionally casting design has relied on speculative techniques, resulting in extended development times (Choudhari et al., 2014). Computer Aided Design (CAD) is useful to handle design iterations (Tu et al., 1995). Numerical simulation methods provide an alternative to physical trials (Stefanescu, 2015). Techniques like GVM (Gradient Vector Method), FVM (Finite Volume Method), FDM (Finite Difference Method), and FEM (Finite Element Method) etc. are used to solve governing equations for predicting metal flow, temperature, casting defects, and mechanical properties (Fang & Zeng, 2004; Si et al., 2003). Simulation packages like AutoCast, CapCast, Pro-

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Cast, MagmaSoft, Flow3D Cast, SolidCast etc. are available for simulation comparison of these tools is reported in terms of solution methods, hardware requirements, user input, simulation steps, and processing time (Khan & Sheikh, 2016)(Behera & Rabindra, 2010) ,(Arabia, 2018; Vaskova et al., 2011).

Numerical Simulations can effectively identify areas of concern but lack accuracy due to assumptions and generalizations made during input, such as boundary conditions and heat transfer coefficients (Dong, Wang, Zhang, et al., 2024). Additionally, numerical simulation methods are time-consuming as they solve partial differential equations, making them unsuitable for real-time evaluation in production lines(B.Ravi, 2018). Consequently, research is increasingly focusing towards ML a subclass of artificial intelligence which can effectively address these limitations.(Suthar et al., 2023)

ML uses algorithms that learn and improve from data deprived of explicit instructions, to make useful predictions(Plathottam et al., 2023). Its ability to identify patterns in large, high-dimensional datasets has led to applications in different fields like accounting, speech and image recognition, manufacturing etc. In production processes, ML enhances quality, supports decision-making, and aligns with Industry 4.0 and Smart Manufacturing initiatives(Antoniadou et al., 2024; Clancy et al., 2022). In the casting industry, Smart Foundries employ centralized systems for managing customer orders and supply chains, emphasizing remote monitoring and data collection from key segments(Z. Li et al., 2024). This system includes expert systems that optimize casting designs, making ML particularly valuable in casting due to the complexity of the processes involved. (Saxena et al., 2020).

ML applications have been utilized in various casting processes. In Die Casting, ML techniques predict component quality and properties(Dučić et al., 2022). ML is used to determine the optimal gating system size for defect-free casting by employing Application Programming Interfaces that manage nonlinear topology with input parameters like casting conditions and alloy grades for die casting (Duan et al., 2023). The desired mechanical properties of castings depend on alloy content, which can vary due to multiple constituents and charge materials present in the furnace; ML techniques can effectively predict these constituents (Dučić et al., 2020).ML has been applied to modify heat treatment processes, utilizing supervised algorithms to minimize costs while maintaining product quality(Wu et al., 2023). ML applications have successfully created databases for the thermodynamic properties of aluminum alloys.(Yi et al., 2021) ML can be categorized as shown in Fig.2(Plathottam et al., 2023).

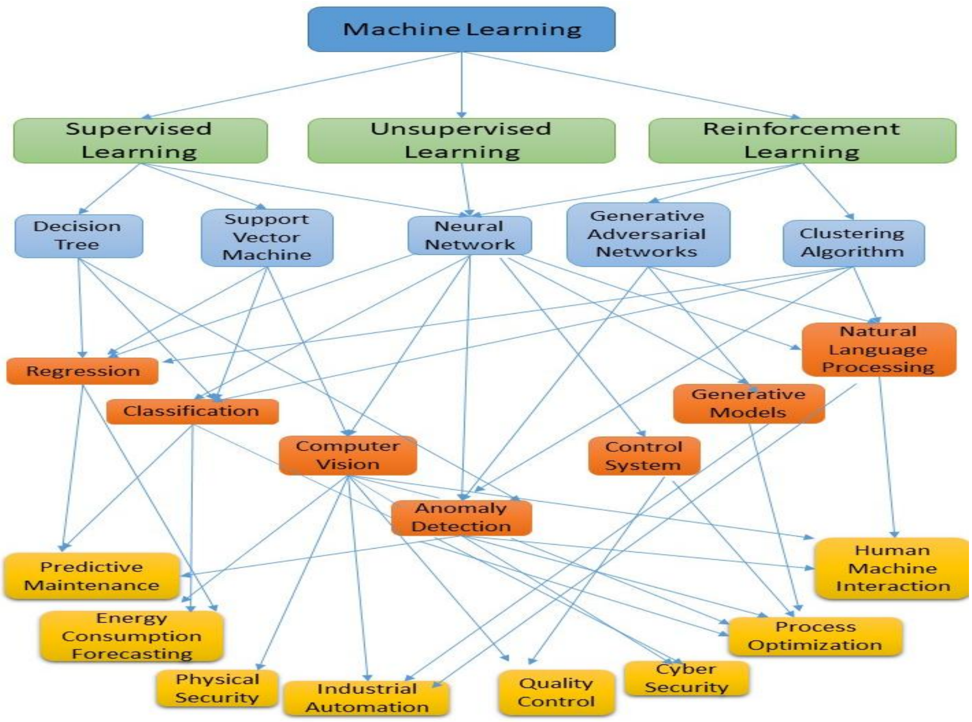

Figure 2 Machine Learning categorization (Plathottam et al., 2023).

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1.3 Theme of Review Paper

Many researchers have worked upon specific sub-process of IC and computational approach for casting(Mayr et al., 2019; Okuniewska et al., 2023); but a comprehensive work related with computational approach applied to IC in classified manner is reported here schematically represented in Fig 3. Here the paper is divided in three sections which are 1) Pre-filling stage that deals with review related to sub- processes prior to filling stage. It is followed by filling stage which deals with gating system design related review work and parameters affecting complete filling. Post filling stage includes knock followed by inspection related to defects and assessment of mechanical properties.

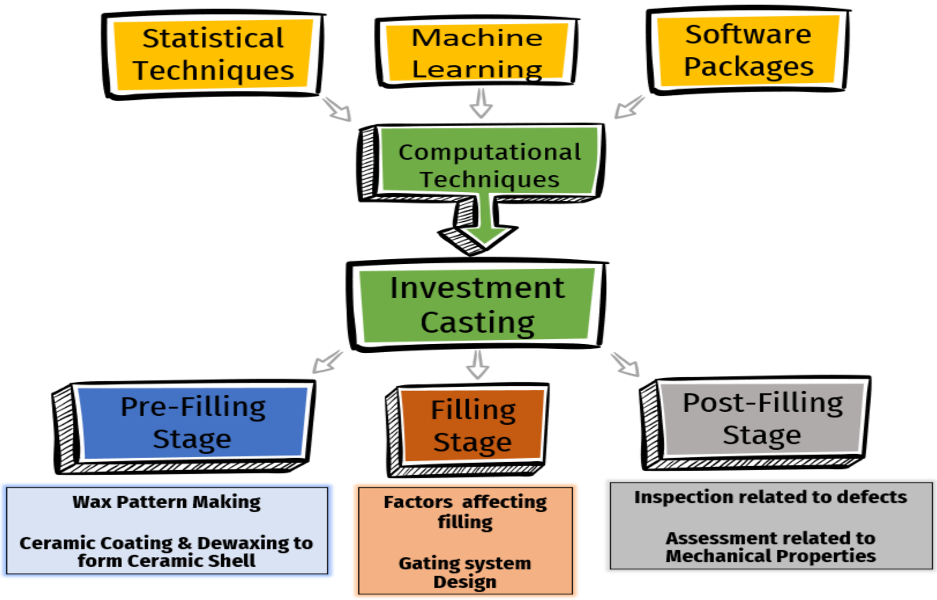

Figure 3 Research Theme

The research paper reviewed for each stage can be inferred from Fig. 6 a), whilst Fig. 6 b) represents proportion of research papers reviewed for computational approaches. The objectives of this review paper are:

1) To explore the computational methods reported for IC.
2) The study explores how process parameters and computational methods impact ceramic shell mold filling and gating system design
3) To review implemented computational approaches to post-filling processes.

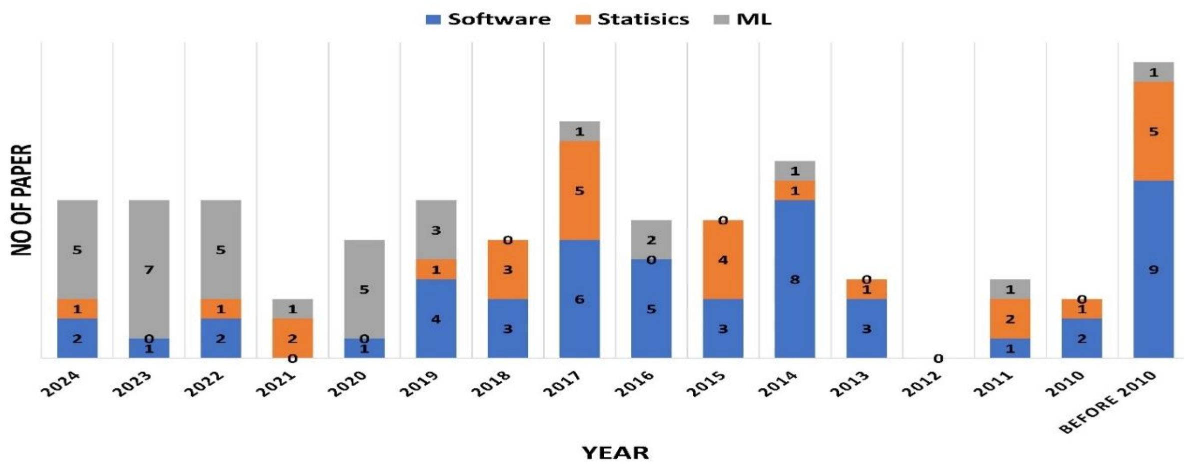

Figure 3 Chronological paper counts of research paper for classified Computational Approaches for IC

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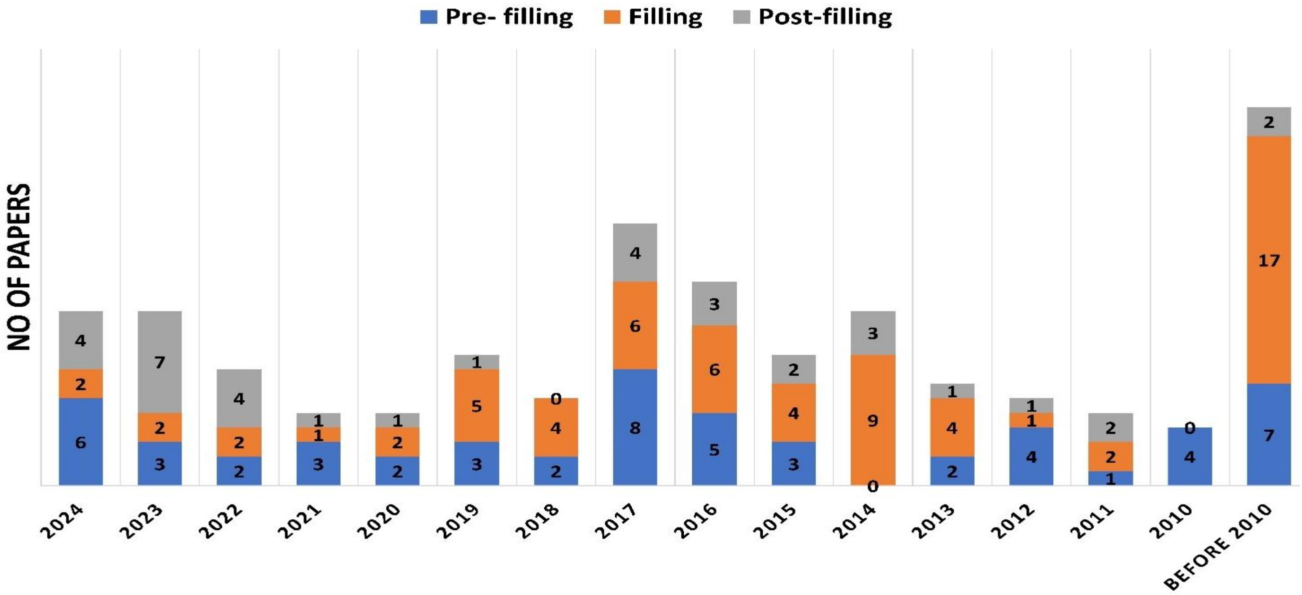

Figure 4 Chronological paper counts of research paper for IC sub-processes.

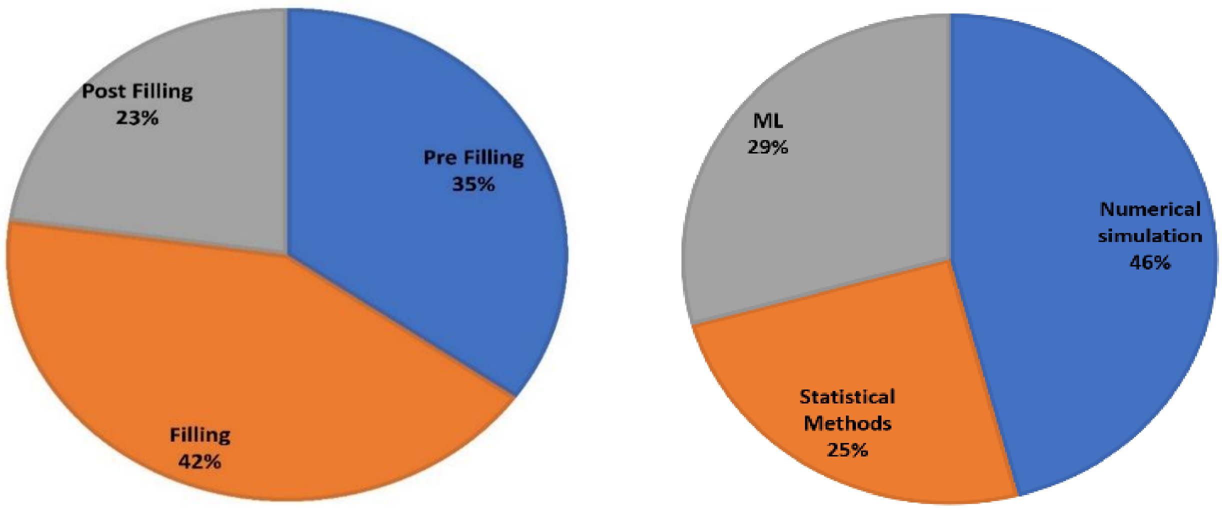

Figure 6 Proportional representation of research papers for a) IC sub-processes b) Computational Approaches

COMPUTATIONAL APPROACHES FOR PRE- FILLING STAGE

Pre-filling stage includes processes prior to filling stage which starts by Wax pattern making; first step of IC; it characterizes outline of actual casting. Molten wax of 55^{o}C- 65^{o}C is injected into metal die to fill metal die cavity(S. Singh & Singh, 2016). Properties of wax like volumetric expansion, melting point, ash content, resistance for creep etc. impact the performance (Sabau & Viswanathan, 2003).Once wax pattern is generated number of such patterns are assembled together to form a wax tree. Ceramic coating is next step, requiring multiple layers of coating (primary, backup, and seal) with stuccoing in between. Stuccoing serves to minimize stresses, provide a rough surface for mechanical bonding between layers, and maintain permeability by increasing particle size with each coat (Jones & Yuan, 2003)

Dewaxing is the next step to produce vacant space in which liquid metal is filled known as ceramic shell mold(Richards et al., 2004). To achieve dimensional accuracy; dimensional changes during various sub-process need to be considered as dimension of product are of reduced size than die because of solidification of wax and alloy [53] ,[54], [55] [56] as schematically represented in Fig. 11.

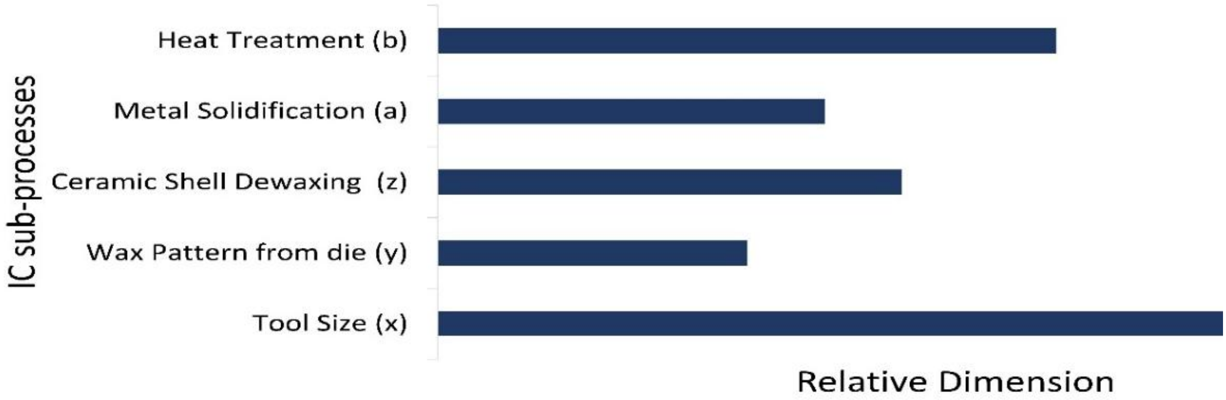

Figure 11 Relative Dimensional changes in IC for sub- processes (Liu et al., 2015)

2.1 Wax Pattern

Sabau et al have reported the prediction of Shrinkage Factor (SF) for wax pattern of stepped component with conclusion:

- **Width SF:** The SF in width was largest near the more massive (thicker) region and it decreased as progressed toward the thinner region.
- **Length SF:** The SF in length was more significant at the edges in comparison centreline.
- **Overall SF:** When casting was subjected to restraint (with holes), SF increased in both width and length directions compared to an unrestrained situation.

Non-uniform SF method was reported to address limitations of linear scaling; for manufacturing of turbine blades(Sabau, 2006). SF is non-homogenous for turbine blades having complex structure. Numerical Simulation and experimental data validated accurate turbine blade based on structural identification method to model the displacement field of different geometrical structures(Yiwei et al., 2017). State Space Model for dimensional control is proposed to manage dimensional changes across stages, including wax pattern, shell expansion, and alloy solidification (Liu et al., 2015). SF varies across different parts of a casting due to differences in macroscopic structures and internal stress distribution. A case study using ProCAST revealed that wheel divided into sections based on structure model demonstrated strong performance in predicting SF across different parts. (Bu et al., 2017).Reverse engineering method for a turbine blade compensates for nonlinear shrinkage by adjusting the cavity profile using displacement data, effectively enhancing quality(D. H. Zhang et al., 2010). Wax injection process; comparison of experimental measurements and predictions showed only a 0.32% average difference in dimension (Wang et al., 2016)**.**

Model of the wax injection process showed qualitative agreement with experimental data for filling time and SF with discussions on optimizing injection gate locations(Taylor et al., 2013). Simulation results using MoldFlow and Flow-3D packages for IC; with predictions found to align well with experimentally observed defects.(Gebelin et al., 2003)**.** Metal-powder injection molding using ANSYS FLOTRAN module, found side gates ensured more uniform flow and temperature compared to top gates (J. Jin & Ning, 2010). Wax SF prediction by Back propagation Artificial Neural Network (BP- ANN) is reported with higher fitting precision than regression method (Tian et al., 2018). Deformation at the trailing edge of turbine blade reached 0.4192 mm implementing suggested single step reverse compensation method reduces maximum deformation by 68.2% so that it reaches 0.15 mm as per requirements (Ren et al., 2023a).. Hybrid metaheuristic approach combining Random Forest (RF) with dung beetle optimization resulted in a 22.4% reduction in prediction error compared to conventional models for thickness of turbine blade at various

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locations.(Dong, Wang, Zhang, et al., 2024). Support Vector Machine (SVM) and BP-ANN were compared ;SVM gave better prediction in comparison with melting temperature of wax as most influencing parameter(Wang et al., 2019)

2.2 Ceramic Coating & Dewaxing to Form Ceramic Shell Mold

Metal-mold interaction involves a reaction amongst alloy and the mold wall, leading to an uneven casting surface with presence of ceramic material(Jones & Yuan, 2003). Ceramic slurry consisting of needle coke demonstrated an improved retention rate of ceramic slurry along with adequate flexural strength and moderate inner surface smoothness with higher permeability (S. Kumar & Karunakar, 2021a). Alumina-silicate materials achieve a modulus of rupture strength of 94 kg/cm², significantly higher than the 49 kg/cm² observed in fused silica sand shell with almost same drying time (Kaila & Dave, 2021)For nickel super alloys reaction between the mold and the molten alloy can be minimized by varying mold composition, thereby reducing chemically induced defects(Kanyo et al., 2020a). Non-conventional ceramic coating using fumed alumina binders and alumina sand back-ups offer higher dimensional stability and better mechanical strength compared to traditional systems(Neto et al., 2017)

Non-uniform ceramic shell mold thickness inversely varies with surface quality and accuracy, ultimately affecting the reliability and value of the final products (Dong, Wang, Cui, et al., 2024). Organic fiber-based shells exhibited higher fired strength ,3 times permeability and 15% greater shell thickness, allowing for fewer coatings on the wax and reducing lead time but lower green strength (Yuan et al., 2012). Mixture of polyethylene wax powder and betel nut fibers was used for the ceramic shell's principal and backup layers. This combination increased green strength by 33%, fired strength by 3%, porosity by 86%, and permeability by 27% (Pattnaik & Sutar, 2022). Singh et al. reported that contributions to dimensional accuracy was 77.84% from the number of slurry layers, 9.95% from the type of pattern material, and 11.63% from the addition of nylon fibers in the first, second, and third coats (R. Singh et al., 2014). Count of ceramic coating contributes 80% to shrinkage defect with other parameters, such as filling time & temperature and cooling rate were insignificant in this context(S. N. Bansode et al., 2019). Dewaxing is a critical stage in IC, as it involves removing wax from ceramic coated tree without any major dimensional changes or cracks. Root Cause of ceramic shell deformation is crucial for achieving dimensional accuracy(S. Jin et al., 2017; Lee et al., 2015) . Most ceramic shell mold failures occur during dewaxing stage due to intensive thermal stress at the interface of ceramic shell mold and wax; as wax typically expands more than ceramic shell leading to cracking or deformation of the shell(Pattnaik et al., 2012). Reversal Solidification Path Dewaxing method resulted with 3 times strength and ability to withstand thermal shock (Mishra & Ranjana, 2010). Lee et al. reported that autoclave dewaxing develops highest strength, surpassing the strength of shells dewaxed by refrigeration. Incomplete removal, along with the curing of the sol during the autoclave process, contributed to the higher strength observed (Lee et al., 2016). Two major stress types in ceramic shells: (a) thermal stress from temperature differences between the interior and exterior mold surfaces, (b) stress from the weight of alloy. COMSOL analysis showed higher stress and cracking at thinner corners (3.45 mm) than flat surfaces (4.74 mm) (Behera et al., 2019).

Ceramic shell must have following characteristics so as to preserve the integrity and quality of final casting :

- Permeability: Air and gases can outflow easily.
- Strength: Dewaxing without failure
- Thermal resistance: Endure thermal stress
- Stability: Inertness for metal and mold chemical reaction.
- Thermal conductivity: Adequate heat transfer and cooling (Jones & Yuan, 2003)

The ceramic shell mold has about 25-62% so that air and gases can outflow easily. (Ding & Dongliang, 2007). Conclusion from key papers are as per Tab.1 .

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Table 1 Gist from key papers of Computational Approaches for Pre-filling stage of IC

Sr No	Author & Year	Type	Process	Parameters Considered	Conclusion
1	(Dong, Wang, Zhang, et al., 2024)	S & E	W	Prediction of Dimensional Accuracy based on wax profile by ML	22.4% decrease in predicted errors with respect to conventional methods
2	(Ren et al., 2023b)	S & E	W	Dimensional Accuracy, deformation at different sections for turbine blade	Reverse Compensation method decreased the maximum deformation by 68.2 %
3	(Pattnaik & Sutar, 2022)	E	CD	Permeability, fired strength and green strength with addition Polyethylene Wax powder and Betel Nut fibers	Improved properties for flexural strength were 33%, fired strength 3 %, permeability 27% and porosity of 86%.
4	(S. Kumar & Karunakar, 2021b)	E	CD	Drying Time, Rupture strength of alumina silicate and fused silica.	Alumina-silicate materials achieve a modulus of rupture strength of 94 kg/cm^2, significantly higher than the 49 kg/cm^2 fused silica sand.
5	(Kanyo et al., 2020b)	R	CD	Strength, thermal resistance, corrosion resistance, dimensional accuracy and permeability	Varying mold composition, ceramic processing can improve required properties.
6	(S. N. Bansode et al., 2019)	S & E	CD	Number of slurry coatings, filling type & temperature along with solidification method	Number of slurry coatings have 80 % contribution towards shrinkage deviation.
7	(Behera et al., 2019)	S & E	CD	Solidification time & Thermal stress of ceramic mold	Defects can be reduced by appropriate simulation techniques.
8	(Tian et al., 2018)	S & E	W	Dimension of component, SF prediction using ML	Contour section shrinkage was different than predicted
9	(Bu et al., 2017)	S & E	W	Structural parameters influence fractional shrinkage.	Relation between fractional shrinkage and structure parameter is non-linear.
10	(Yiwei et al., 2017)	S & E	W	Shrinkage factors for turbine blade of wax pattern	Non-uniform shrinkage distribution is more accurate than linear scaling method

R: Review paper, S: Simulation, E: Experimental, W: Wax Pattern &Properties, CD: Ceramic Coating & Dewaxing

COMPUTATIONAL APPROACHES FOR FILLING STAGE

Filling stage includes pre-heating of the ceramic shell mold, filling of alloy along with considering the design aspect and factors affecting the complete filling. Various factors significantly impact the quality of the final cast product, including fluidity, solidification time, pouring time, critical velocity (Vcri) for turbulence, filling manner, alloy filling temperature and heat transfer coefficient (Federico Arduino et al., n.d.; Rafique & Iqbal, 2009).

3.1 Factors Affecting Filling

Fluidity, defined as the distance traveled by molten metal before solidification, it's a crucial factor for ensuring complete filling of ceramic shell mold; a primary requirement to obtain quality products(X. Zhang & Chen, 2005).

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For thin-wall castings like in IC , around 80% defects are due to improper filling and design of gating system(Raza et al., 2018).Length of fluidity is determined by an empirical relation for a specific arrangement, which depends on alloy properties like density, velocity, enthalpy of fusion, degree of superheat, filling temperature, filling head, specific heat capacity, heat transfer coefficient, ceramic shell mold pre-heat temperature, permeability , thermal conductivity, geometry of component etc. (Fleming. Niyama, 1963),(Ravi et al., 2008).

To achieve complete filling, higher flow velocities are favorable, but if it exceeds the critical velocity, turbulent flow may occur, leading to detrimental effects such as inclusions of mold material and porosity if adequate venting is unavailable (Reilly et al., 2013). Campbell expressed that Vcri is proportional to the fourth power of the ratio of surface tension to density. Vcri for nonferrous alloys is 0.4 - 0.6 m/s whilst for ferrous alloys is 1m/s (Jolly, 2005). Higher pouring and mold temperatures can enhance fluidity; however, excessively high pouring temperatures can prolong solidification, leading to the formation of coarse grains and an increased risk of hot cracking. Conversely, reducing pouring and ceramic shell mold temperatures may prevent hot cracking but can hinder complete cavity filling if temperatures are too low; careful balance is essential(Mingguang, 2017). Solidification time for IC was estimated by lumped model for finite volume-based numerical simulations analytically. It under predicted the time in comparison with actually measured values but still provide basis of knowledge (Chattopadhyay, 2011).

Top and bottom filling systems for non-ferrous alloys was investigated in which the Weibull modulus improved from 18 to 34 with bottom filling system, indicating enhanced reliability and reduced oxide damage (Cox, 2000). A study on top and bottom filling systems for turbine blade casting highlighted that while top filling is easier to construct, it often causes defects like inclusions (30%), porosity (20%), hot cracks (10%), and misruns (10%) due to turbulence. (D. Z. Li et al., 2004). Fluidity for top filling is highly dependent upon on filling temperature whilst ceramic shell mold pre-heat temperature is insignificant. In contrast, bottom filling configuration demonstrated greater stability, with fluidity remaining relatively unaffected by variations in filling and shell pre-heat temperature with reduced porosity and defects compared to the top filling system (Kuo & Huang, 2017a). Change in dimension of products for IC; filling temperature accounts for 68.38%, the slurry layer combination for 6.57%, and the modulus for 23.12% mentioned parameters (R. Singh & Singh, 2017)

3.2 Gating System Design

Traditionally, gating system design in casting has relied on trial-and-error methods, leading to extended development times. The gating system includes cup, sprue, feeder, runner, and ingates, significantly impacts casting yield, defect rates, and the mechanical properties of products (Sata & Maheta, 2021). Numerical Simulation methods reduce scrap and promote defect-free castings, making them more viable than traditional approaches. Design of the gating system significantly impacts the yield and overall performance of IC (Chalekar et al., 2015). Porosity & shrinkage defects were predicted by applying an explicit finite difference method with component-wise splitting to titanium dental casting systems; matching experimental data for various casting types (X. P. Zhang et al., 2006). Numerical simulation of titanium alloy thin-wall casting for shrinkage defect distributions, with results closely matching X-ray experimental data (Tao et al., 2018). Flow-3D package was used to determine values for filling velocity and filling time; demonstrating its impact of gating system design for final cast product (Ramnath et al., 2014). Authors revealed that 53.6% of defects are related to incomplete filling, particularly cold shuts and misruns mostly at upper levels of the tree. Experimental validation of reverse tapered sprue design generated non defective casting as predicted by MagmaSoft due to decrease fluctuation filling velocity (Thammachot et al., 2013). To achieve accurate simulation results, precise boundary conditions and input parameters are essential; but exact values are often difficult to measure. The use of reverse engineering by adjusting simulation models to correlate parameters is reported for industrially manufactured parts(Anglada et al., 2013).AnyCast predicted that probability of shrinkage defects increased with lower filling and shell pre-heat temperatures and increased cooling rate(P. Huang et al., 2014). Shrinkage and misrun in thin-section impellers can be effectively eliminated by optimizing the gating system design based on ProCAST simulation results (F. Li et al., 2020). Sangita Bansode et al. reported that improper gating system could cause cracks and increase lead times by using SOftCAst also affecting post-casting operations.(S. Bansode et al., 2017)

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Authors revealed positive effect with increasing filling temperature whilst feeding time and ceramic shell mold pre-heat temperature showed no significant correlation using MagmaSoft, by varying parameters like component orientation (0° to 90°), feeder length, feeder diameter, insulation diameter around the feeder with 2 mm increase whilst filling temperature (1690 to 1740°C in 5°C increments)(Fourie, 2014). Resizing radius of the gating system rather than height was most effective resizing strategy, resulting in a 47.85% reduction in gating system volume and a 15.02% increase in casting yield (Wang et al., 2018). Bottom feeding in IC significantly reduces oxide films and shrinkage by 90%, enhancing reliability compared to top filling(Bruna et al., 2019). ProCAST effectively identifies porosity in titanium alloy gearboxes through precise modeling, and incorporating low-cost alloys into titanium shows minimal impact on mechanical properties of the product (Liao et al., 2022).

Radial Basis Functions neural network, a statistical technique along with Design of Experiments proves to increase the yield by 14.91% with input parameters as filling temperature, ceramic shell mold pre heat temperature, diameter & length of main sprue heat transfer coefficient and velocity (Yu et al., 2020).Lower ceramic shell mold temperature improves strut microstructure and energy absorption but reduce ceramic shell mold filling and negatively impacting overall mechanical properties(Firoozbakht et al., 2023); To ensure ovality as per expectation based on data driven method filling temperature was 1500.5 °C, ceramic shell mold pre-heat temperature 1052.5°C, and 1.7258% allowance in pattern dimension were recommended(Donghong et al., 2022a). to conclude gist from key papers of computational approaches for Filling stage of IC is as per Tab.2.

Table 2 Gist of Computational Approaches for filling stage of IC

Sr No	Author	Type	Processes	Parameters Considered	Conclusion
1	(Chen et al., 2024)	S & E	C	Ceramic shell thermal conductivity, kinematic viscosity & Fluidity	Improving the thermal conductivity and fluidity reduced the cold shut defect from 42.6 % to 0 %.
3	(Donghong et al., 2022b)	S & E	F	Pouring temperature, shell pre heat temperature and shrinkage factor	Shell preheat temperature is most influencing factor for dimension variation in terms of ovality
4	(F. Li et al., 2020)	A & E	F	Filling temperature & time, shell pre-heat temperature and porosity	Shrinkage porosity for thin-walled casting was eliminated by utilizing optimized results from Taguchi method
6	(Bruna et al., 2019)	S & E	G	Dimension of Gating system	90 % decrease in porosity by increasing filling head.
7	(Wang et al., 2018)	E & A	G	Dimension of gating system, Filling temperature, shrinkage volume, length of porosity from casting,	Diameter of gating system significantly affects the shrinkage volume and location of porosity, with shrinkage volume being more sensitive than distance. Improvement of 15.02 % in yield is obtained by decreasing gating system volume by 47.85%.
9	(Mingguang, 2017)	S &E	F	Hot cracking defect due to pouring temperature and mold temperature	Hot cracking occurs when thermal stresses exceed yield strength; although a high pouring temperature ensures complete filling during prolonged solidification, it increases the risk of hot cracking
10	(Kuo & Huang, 2017b)	S & E	G	Niyama Criterion and Retain Melt Modulus method for defect prediction	The velocity of different arrangements was evaluated in conjunction with time-temperature and time-solidification fraction graphs to achieve maximum yield

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Sr No	Author	Type	Processes	Parameters Considered	Conclusion
11	(P. Huang & Lin, 2016)	S & E	G	shell mold temperature & thickness, pouring temperature& Time and number of calculation grids.	Pouring temperature had more profound effect than mold temperature on shrinkage. Shell Thickness affected cooling rate hence fluidity.
12	(Raza, 2015)	E	F	Fluidity by Top and bottom filling for thin wall castings	Top filling fluidity is sensitive to casting temperature, whereas bottom-gated configurations maintain stable fluidity regardless of casting or mold preheat temperature

S: Simulation, E: Experimental, F: Factor affecting filling, G: Gating system design

COMPUTATIONAL APPROACHES FOR POST FILLING STAGE

This stage involves the knockout process, where components are removed from the tree, followed by defect inspection and overall analysis of IC explore improvement opportunities. Minimum and maximum principal stress values at ingates were determined and verified experimentally by providing vibrations so that failure occurred at desired locations (Kuo & Huang, 2017b). Residual stresses are less in magnitude for casting process but still are important to study as they can lead to failure of cast component. Maximum Residual Stress value of 7.015* 10^9 N/m² was found to be reduced to 6.352 * 10^9 N/m² by shape alteration obtained by numerical simulation (Keste et al., 2015).

4.1 Inspection Related to Defects

X-ray techniques are used to detect defects but are material dependent hence for titanium casting a novel approach of neutron radiography is reported which uses gadolinium oxide in face coat. Probability of detection improved 3 times for inclusions(Richards et al., 2004). Genetic algorithm and neural networking were used to find the best fit for input parameters of pouring temperature and shell preheat heat temperature with output measurement as complete filling and solidification time(Vosniakos et al., 2005). Image processing can significantly enhance the inspection process by improving accuracy and efficiency.

An inspection device has been reported with the potential to outperform human inspection, providing more reliable results by SVM classifier(Costa et al., 2020).The Naive Bayes models like Gaussian, Multinomial, Complement and Bernoulli were examined to effectively detect defects of IC products prior to production (Sawant & Agashe, 2022).

Deep learning-based device was examined by different methods with training of 36000 images for defect identification. Residual Neural Network demonstrated the highest accuracy and so was successfully implemented for efficient industrial defect detection (Yousef & Sata, 2024a). Surface discontinuities in aluminum castings were inspected using automated image capture along with Gaussian filtering for noise removal, and feature extraction techniques. Trained on 1400 images and tested on 350 images, SVM outperformed K- Nearest Neighbor (KNN) in accuracy.(Yousef et al., 2022). U-Net algorithm with image segmentation achieved 81% dice coefficient; to detect defect size on casting surface (Yousef & Sata, 2024b).

Slurry pump made by IC had shrinkage defect which was rectified by adjusting riser placement rather than riser dimension (Zhi et al., 2014). Hardin et al. emphasized the unreliability of deterministic optimum designs in casting without considering statistical and physical uncertainties. Reliability Based design considering variations of input parameters 7% yield improvement with a significantly lower failure probability of 4.6%. (Hardin et al., 2015).

4.2 Assessment Related to Mechanical Properties

Bayesian Inference a probabilistic approach analyzed process variables like ceramic shell mold material properties, drying conditions, pre-heat temperature and mechanical stresses to predict deformation issues, identify root causes

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and suggest mitigation measures. It enabled early defect detection and process optimization, improving casting reliability and quality (S. Jin et al., 2017). Taguchi method was reported for improving the quality of IC by optimizing process parameters like shell pre-heat temperature, filling temperature and stirring current with output measured for shrinkage and tensile strength(Pattnaik et al., 2015).Mechanical properties of IC products were predicted using Artificial Neural Network and Multi Variate Regression (MVR) models based on filling factors and alloy chemical composition data from 800 heats. While both approaches performed well, MVR yielded slightly better results(Sata & Ravi, 2014)

Integration of ML and computational thermodynamics enhances manufacturing of aluminum alloys such as Al-Si-Mg and modified A356 alloys. By employing a microstructure-properties matrix trained through ML, researchers can better understand the strengthening and toughening mechanisms in aluminum casting alloys. This combined approach is expected to improve the manufacturing process and application of alloys(Yi et al., 2021). Mechanical properties are traditionally assessed through destructive testing, a process that is time-consuming and wasteful. To address this, techniques like Least Absolute Shrinkage Selection Operator and Variable Selection Using Random Forests were employed to identify significant variables from 25 independent variables. The performance of selected features is evaluated using ML models like RF, KNN and Extreme Gradient Boost(XG-Boost). Tree-based algorithms, particularly XG-Boost and RF, demonstrate strong predictive capabilities, minimizing the need for destructive tests and thereby reducing material waste and enhancing productivity in the foundry environment.(Jaspal Virdi, 2019); to conclude gist from key papers of computational approaches for Post-filling stage of IC is as per Tab.3

CONCLUSION AND FUTURE SCOPE

5.1 Conclusion

Investment casting involves numerous variables that impact the quality and yield of the final casting. These variables span across various sub-processes like tool dimensions considering shrinkage factor, wax properties like melting temperature, injection pressure, injection time, viscosity, surface tension and material content. Number of coatings, humidity for soaking, time of soaking, temperature of soaking face coat, seal coat, green strength, fired strength of shell, permeability. Dewaxing should occur without shell cracking, also wax should be reusable with appropriate strength of shell. Filling temperature & time, degree of superheat, shell pre-heat

Table 3 Gist of Computational Approaches of Post Filling stage of IC

Sr No	Author	Type	Processes	Parameters Considered	Conclusion
1	(Yousef & Sata, 2024a)	S &E	DA	U-net algorithm surface defect detection & sizing image segmentation.	U net gives 81 % dice coefficient in detecting surface defects along with evaluating severity of defects.
3	(Yousef et al., 2022)	S &E	DA	Surface discontinuities, SVM, KNN	SVM gave better results in comparison with KNN
4	(Costa et al., 2020)	S &E	DA	RANSAC algorithm, SVM for image classification	99 % accuracy is reported for circle and line defects
5	(Del Vecchio et al., 2019)	S & E	DA	Melting temperature at different heights in furnace SVM	Mean value of temperature features for defect free avoiding an attribute casting were ranked.
6	(Jaspal Virdi, 2019)	S & E	MP	UTS, YS and % Elongation, XG-Boost & RF	RF and XG-Boost represents capability to eliminate destructive testing
7	(B.Ravi, 2018)	S & E	MP	UTS, YS and % Elongation	Range of parameters was determined by Bayesian Inference to obtain desired casting.

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Sr No	Author	Type	Processes	Parameters Considered	Conclusion
8	(Kuo & Huang, 2017b)	S & E	KO	Maximum and Minimum principal stress at ingates	Breaks occurred at the ingates notches due to vibrations, with predicted stress values matching actual results.
9	(Hardin et al., 2015)	S	MP	RBDO in design variables to meet a stated target.	RBDO improves yield by 7% with 4.6% failure probability in comparison of 12 % improvement with 61 % failure probability
10	(Zhi et al., 2014)	S & E	DA	Position of riser and machining allowance for shrinkage defect	Appropriate position rather dimension can eliminate shrinkage defect with appropriate machine allowance

S: Simulation, E: Experimental, MP: Mechanical Properties, KO: Knock out, DA: Defect Analysis UTS: Ultimate tensile Strength, YS: Yield Strength, EL: % Elongation, RF: Random Forest, SVM: Support Vector Machine, KNN: K-Nearest Neighbor, XG-Boost: Extreme gradient boosting, MVR: Multivariate Variate Regression, ANN: Artificial Neural Network

Table 4 Decision matrix

Sr No	Author	PRE- FILLING									Filling Stage									Post Filling									Computation Technquies																				
		Wax Pattern				Ceramic Coating & Dewaxing					Factors Affecting Filling								GD	DA	Defect Analysis							MP	Software Packages							Statiscal Tools					Machine Learning								
		WP	WIP	WIV	WIT	CCP	NC	D	TPS	SF	F	FV	FT	PT	ST	Pte	SPT	CCA	GD	DA	S	P	M	HT	HS	SD	OD	MP	ProCast	Nova	SoftCast	Magmasoft	Ansys	AnyCast	Other Software	DOE	ANNOVA	Bayesian	RSM	Other technquies	SVM	PCA	RF	XGBOOST	KNN	DL	ANN	IP	Other
1	Yousef et al 2024 [155]																									*																						*	*
2	Dong et al 2024[13]	*																		*																		*			*		*		*				
3	Chen et al 2024 [106]								*		*				*												*		*																				
4	Dong et al 2024 [70]					*	*													*																													
5	Dai et al 2024 [156]					*	*		*																																								
6	Stepan et al 2024 [80]					*		*	*																																								
7	Yousef et al 2023[27]																									*												*								*		*	*
8	Yousef et al 2023 [146]																									*															*				*				
9	Suthar et al 2023[15]						*		*					*		*	*			*								*													*		*		*				*
10	Ren et al 2023[89]	*								*										*									*																				
11	Firoozbakt et al 2023[137]															*	*	*										*																					
12	Yousef et al 2022[147]																									*																							
13	Liao et al 2022 [157]								*					*	*	*	*		*		*				*		*		*																				
14	Donhong et al 2022 [138]								*	*						*	*			*									*							*		*	*										
15	Clancy et al 2022[17]						*																																	*									
16	Sawant et al 2022[145]																				*																												*
17	Kumar et al 2021[90]					*			*																																								
18	Kaila et al 2021[68]					*			*																																								
19	Zhang et al 2021[127]													*		*	*				*	*																											
20	Ren et al 2021[158]						*		*						*	*	*			*									*																				
21	Costa et al 2020 [143]																			*																					*							*	
22	Yu et al 2020 [136]															*	*		*			*							*							*					*								
23	Huang et al 2020 [36]	*				*			*																																								
24	Kanyo et al 2020[91]					*	*	*	*																																								
25	Fei Li et al 2020[126]											*		*	*	*	*		*		*								*																				
26	Wang et al 2019 [66]	*	*	*	*					*										*																					*						*		
27	del et al 2019[142]															*		*		*																					*								

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Sr No	Author	PRE- FILLING									Filling Stage									Post Filling									Computation Technquies																				
		Wax Pattern				Ceramic Coating & Dewaxing					Factors Affecting Filling								GD	DA	Defect Analysis							MP	Software Packages							Statiscal Tools					Machine Learning								
		WP	WIP	WIV	WIT	CCP	NC	D	TPS	SF	F	FV	FT	PT	ST	Pte	SPT	CCA	GD	DA	S	P	M	HT	HS	SD	OD	MP	ProCast	Nova	SoftCast	Magmasoft	Ansys	AnyCast	Other Software	DOE	ANNOVA	Bayesian	RSM	Other technquies	SVM	PCA	RF	XGBOOST	KNN	DL	ANN	IP	Other
28	Virdi et al 2019[154]		*	*		*	*		*					*		*	*	*		*	*	*						*													*	*	*	*					
29	Bansode et al 2019[74]						*						*			*	*		*		*				*						*						*													
30	Behera et al 2019[81]						*	*	*						*																		*																
31	Raza et al 2018 [113]						*									*	*			*			*																										
32	Tian et al 2018[64]						*									*	*												*											*							*		
33	Wang et al 2018[132]															*	*		*			*							*										*										
34	Kansagra et al 2018[159]																		*		*	*			*						*																		
35	Tao et al 2018[120]											*		*	*	*	*				*						*																						
36	B. Ravi et al 2018[153]			*	*	*	*		*					*	*	*		*			*		*															*											
37	Singh et al 2017 [114]						*									*			*	*																												
38	Sata et al 2017[151]			*	*	*	*		*							*	*	*		*	*	*	*					*																					
39	Yiwei et al 2017 [56]									*					*					*									*																				
40	Kuo et al 2017[111]						*							*	*	*	*		*	*	*													*															
41	Mingguang 2017[105]											*		*	*	*	*		*	*									*																				
42	Jin et al 2017[77]					*	*	*	*																													*											
43	Bu et al 2017[58]									*									*	*									*																				
44	Lee et al 2016[79]						*	*	*																															*									
45	Huang et al 2016 [128]													*	*	*	*		*	*														*															
46	Wang et al 2016 [60]				*				*	*										*									*																				
47	Mahrabi et al 2016[46]						*	*	*								*		*										*																				
48	Kumar et al 2016[42]						*		*										*	*																	*												
49	Raza et al 2015 [112]						*		*							*				*										*																			
50	Chalekar et al 2015[95]									*									*	*	*														*														
51	Liu et al 2015 [57]	*							*	*										*																				*									
52	Fourie et al 2015[130]						*		*	*		*	*	*		*	*		*	*	*											*																	
53	Keste et al 2015 [140]								*							*											*						*																
54	Hardin et al 2015 [150]															*				*												*								*									

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		Wax Pattern				Ceramic Coating & Dewaxing					Factors Affecting Filling								GD	DA	Defect Analysis							MP	Software Packages							Statiscal Tools					Machine Learning									
		WP	WIP	WIV	WIT	CCP	NC	D	TPS	SF	F	FV	FT	PT	ST	Pte	SPT	CCA	GD	DA	S	P	M	HT	HS	SD	OD	MP	ProCast	Nova	SoftCast	Magmasoft	Ansys	AnyCast	Other Software	DOE	ANNOVA	Bayesian	RSM	Other technquies	SVM	PCA	RF	XGBOOST	KNN	DL	ANN	IP	Other
55	Singh et al 2014 [73]						*													*																				*									
56	Pattnaik et al 2014[75]		*	*	*														*		*					*	*													*									
57	Huang et al 2014[125]													*		*	*		*			*												*															
58	Zhi et al 2014[149]													*	*	*	*		*	*					*				*																				
59	Bazhenov et al 2014[122]								*		*					*		*		*									*																				
60	Jafari et al 2013 [102]					*	*		*								*									*																							
61	Taylor et al 2013[61]	*	*	*	*					*					*				*	*															*														
62	Anglada et al 2013[124]									*					*	*					*								*																				
63	Thammanchot 2013 [123]											*		*	*	*			*													*																	
64	Xu et al 2012 [87]					*	*		*	*										*												*																	
65	Yuan et al 2012 [71]					*	*		*											*																													
66	Chattophyay 2011 [107]														*										*																								
67	Liao et al 2011[160]														*	*	*		*						*																								
68	Najafi et al 2011[34]									*																		*																					
69	Vakova et al 2011[161]														*					*	*	*								*		*																	
70	Jin et al 2010[63]	*		*	*					*									*						*								*																
71	Zhang et al 2010[59]	*								*																														*									
72	Mishra et al 2010[78]							*	*																																								
	Total	8	4	7	7	14	25	7	29	15	2	5	2	14	18	31	24	6	22	32	16	8	3	0	7	6	5	5	17	2	2	5	3	3	2	2	2	5	2	8	8	1	3	1	3	1	2	3	4

WP : Wax Pattern Making, WIP : Wax Injection Pressure, WIV : Wax Injection velocity WIT : Wax Injection Time, CCP : Ceramic Coating & Properties NC: Number of ceramic coatings, D: Dewaxing TPS : Thermo-Physical Properties of shell, SF : Shrinkage Factor F: Fluidity , FV : Filling Velocity , FT: Filling Time, PT: Pouring Time, ST : Solidification Time, Pte: Pouring Temperature, GD : Gating System Design , DA : Defect Analysis, S: Shrinkage, P: Porosity, M: Misrun, HT : Hot Tears, HS : Hot Spot SD : Surface Defects, MP: Mechanical Properties, DOE: Design Of Experiments, ANNOVA: Analysis of Variance, RSM : Response Surface Methodology. SVM: Support Vector Machine, PCA: Principal Component Analysis, RF: Random Forest, XG-Boost: Extreme gradient boosting, KNN: K-Nearest Neighbor, DL: Deep Learning, IP: Image Processing

temperature & time, velocity of filling, solidification time, dimension of sprue, runner, cup and ingates, number of components in a tree, knock out and inspection method. All these parameters must be carefully controlled to achieve high yield and produce quality castings in the IC process with the number of research for each variable is described in 'Table 4' from 72 key research papers.

As can be observed ML has been applied for post filling stage particularly for inspection with about 50 % of stack of total work reported for IC. Software packages are utilized for filling stage with about 57 % of work reported for dimension of gating system for given component to eliminate particularly shrinkage and porosity defects whilst statistics tools are employed for overall improvement of IC. Further gist of review is stated below:

- IC requires high dimensional accuracy. Dimensional changes during each sub-process must be known precisely.
- The linear shrinkage method is not suitable for varying thicknesses and geometries, which are common in IC applications. Structural shrinkage methods provide better results than linear shrinkage for IC applications. Reverse engineering proves to be helpful in this context.
- Simulation models for IC are based on various assumptions regarding material properties and operational methods, which can vary significantly between industries. Hence, experimental verification of results is necessary.
- Gating design starts with modulus methodology, but initial dimensions may not be optimized. Modifications are done through experiments or simulations until defects are resolved.
- Statistical optimization methods can improve IC yield, but they are time-consuming and require skilled labor.
- ML methods are used for prediction of defects and mechanical properties in IC, using supervised learning and image processing techniques.

5.2 Future Scope

ML can be used create expert system that assist in the design process, automating decisions that would typically require the experience of skilled labour. These systems can:

- *Predict defects based on previous casting outcomes*: Defects must be predicted with high accuracy using measurable input parameters from historical data. To handle class imbalance, appropriate method must be used to enhance model reliability.
- *Recommend adjustments in process parameters*: Number of process parameters effect final dimension and mechanical properties of casting. Combination of process parameters must be recommended so as to have desired set of properties and dimensional accuracy prior to production. A hybrid of supervised learning and Reinforcement Learning can be used to dynamically adjust these parameters during production.
- *Optimize gating system designs***:** Appropriate classification of the existing components can be processed to have optimal dimensions of gating system for new components so as to have optimal yield and pin point combinations of process variables for desired output.
- *Image Processing & Supervised Learning*: ML can analyse images of cast components to detect defects and help predict mechanical properties, speeding up the quality control process by eliminating human intervention to increase the reliability in real time production.
- *Automation of Knowledge-Intensive Processes*: Combining supervised learning for decision support with RL for adaptive optimization, these expert systems can significantly reduce dependence on skilled labor, particularly in small-scale industries, while improving consistency, scalability, and decision speed.

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