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AI-driven techniques for controlling the metal melting production: a review, processes, enabling technologies, solutions, and research challenges

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[1] Cabanac G, Labbe C and Magazinov A 2021 Tortured phrases: a dubious writing style emerging in science. Evidence of critical issues affecting established journals arXiv 2107.06751v1
[2] La Fé-Perdomo I et al 2021 Surface roughness Ra prediction in selective laser melting of 316L stainless steel by means of artificial intelligence inference Journal of King Saud University—Engineering Sciences 35 148–56
[3] Tunçkaya Y and Kılıklükaya E 2016 Comparative performance evaluation of blast furnace flame temperature prediction using artificial intelligence and statistical methods Turkish Journal of Electrical Engineering and Computer Sciences 24 1163–75
[4] (https://pubpeer.com/publications/E2A793546AF12841A24F073EAC948A)
TOPICAL REVIEW

AI-driven techniques for controlling the metal melting production: a review, processes, enabling technologies, solutions, and research challenges

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Abstract

Artificial Intelligence has left no stone unturned, and mechanical engineering is one of its biggest consumers. Such technological advancements in metal melting can help in process simplification, hazard reduction, human involvement reduction & lesser process time. Implementing the AI models in the melting technology will ultimately help various industries, i.e., Foundry, Architecture, Jewelry Industry, etc. This review extensively sheds light on Artificial Intelligence models implemented in metal melting processes or the metal melting aspect, alongside explaining additive manufacturing as a competitor to the current melting processes and its advances in metal melting and AI implementations.

1. Introduction

Heating and melting metals into liquids to turn them into the desired shape is complex, including several processes that waste material and energy. These losses are caused by unwanted convection, conduction and radiation, metal loss, and stack loss (fume gases). The magnitude of the losses is determined by the furnace’s design, heating the metals, and the fuel utilized. This makes the foundry one of the most energy-intensive industries due to metal melting being a high energy process that consumes almost 55% of the energy used in the foundry- during metal casting, making it a very costly process. It is because foundries still use inefficient metal melting techniques unaided by Artificial Intelligence. With the use of AI in various steps in the metal melting process like classification of weld pool image, robot-controlled welding processes, predicting the mechanical properties of materials by finding microhardness, tensile strength, etc, in the FSW process for various materials, including but not limited to various Aluminium alloys, predicting the susceptibility of intergranular corrosion in FSR, etc. Incorporating these processes will significantly enhance every step of the metal melting process, which is given below in figure 1.

Changes to the operations and melting process design can impact the subsequent steps, as shown in figure 1. It becomes critical to assess the impact of all modifications across the entire melting process to track the energy consumption if conserving it in one step leads to overburdening [1].

Microwave melting, Solar melting, plasma heating, and infrared heating are examples of emerging technologies that offer unique ways to deliver massive amounts of energy to metals; however, barriers such as a lack of capital resources and melting capacity, as well as necessary space requirements, tends to make such innovations financially burdening for the metal casting and melting industry.

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As a result, the most likely energy-saving advancements in melting technologies are retro-fit upgrades for existing furnaces, such as charge pre-heating, oxygen-enriched fuel combustion, heat recovery from flue gases, and molten metal delivery.

These processes are divided into four successive regimes, eventually approaching a steady-state, and they are:

(i) An initial pure conduction regime,
(ii) A regime that has convection partially in the upper part and conduction in the lower part,
(iii) Pure convection regime,
(iv) Heat extraction from the cold wall influences the melting process.

These are done with the help of eight dimensionless parameters like Stefan number, Nusselt number, Rayleigh number, Aspect ratio, Prandtl number, and sub-cooling parameters [2].
Conduction and convection are more crucial for the melting and solidification of the chosen material [3]. During melting, convection increases the melting rate. However, in solidification, convection decreases the growth of the new phase.

Industry 4.0 promotes advanced information technology and the integration of intelligent manufacturing systems with cutting-edge information technology. Using current manufacturing skills in conjunction with the integration of new information technology significantly impacts economic competitiveness.

2. Understanding the process/literature survey

Casting, joining, forming, machining, surface working, additive manufacturing, and powder metallurgy are the types of the manufacturing process. Fabrication refers to building the required product using one or more aforementioned manufacturing processes. Casting is a manufacturing process where the metal is melted and poured into the desired shape hollow cavity. Metal melting is done through different processes and is classified in figure 2.

The following are some of the criteria that influence furnace selection:

(i) Initial and ongoing costs are taken into account
(ii) Repair and maintenance costs on a relative basis
(iii) The availability of various fuels in the area, as well as their respective costs
(iv) Melting efficiency, particularly melting speed
(v) Metal composition and melting temperature [4]

The growth of the melt layer increases the thermal resistance and tends to lower the heat transfer coefficient. Buoyancy-driven natural convection is the primary reason for phase change boundary, heat transfer, and melting rate [5]. Contingency is a vital heat transfer mechanism when melting pure tin from a vertical wall. Melting tin was done in a rectangular cavity using two opposite walls with heaters [6]. These heaters are made of a 10mm thick copper plate and operate at a constant temperature. The thermal conductivity of tin is higher than other liquids, and the shape and motion of the solid-liquid phase interface are affected by convection and advection.

Melting and solidification are influenced by thermocapillary enhancing or reducing solid-liquid interface heat transfer rates near the bottom and free surface. Control volume-based discretization method is used to predict melting in the presence of natural convection. Enormous numerical predictions are made for melting pure metal with both surface tension forces and buoyancy. Local melting behavior is affected by thermocapillary forces [7]. Solid-liquid interface shapes are calculated using the pour-out method and the probing method. The freezing rate decreases as the natural convection increases [8]. As the undercooling increases, the solid-liquid interface energy decreases [9]. During the melting of porous silica glass, the melting temperature of the pores decreases when the pore size increases. The latent heat was less in small pores, and the enthalpy of fusion was found by measuring the heat released or absorbed at the solid-liquid transition [10]. The mean pore diameter (d) is determined using the equation (1),

![Figure 2. Classifications of metal melting furnace.](image-url)
During the melting of pure gallium from a vertical wall in a cuboid cavity, walls in 3D simulation suppressed the flow and created weak turbulence, which prevented the formation of a multicellular flow pattern. In the 2D simulation, there are no walls in the third direction, so multi-vortex structures were present at the beginning of melting. These analyses address the phase change problems and the influence of different cavity aspect ratios [11].

The transition elements are used due to their structural stability. Elements like V, Ti, Cr, Ta, Mo, W, Co, Fe, and Ni are considered and tested with different ambient conditions. High-pressure diamond anvil cell (DAC) studies with the help of X-ray diffraction methods. BCC, HCP, and FCC are the structures of the transition element. BCC structures have high stability in their structures. This property allows us to test melting in the BCC phase for a wide pressure range. Fe is the only element that has gotten greater attention in high-pressure research. Melting points for a few elements have been found using interpolation from the graph and data obtained. It is observed that a close-packed solid has a smaller melting temperature than BCC solid. Since the energy of the close-packed structures is less than thermal energy near melting, they cause defects in the product. These defects caused may lead to a lowering of the perfect lattice melting temperature [12].

2.1. Furnace-based melting

Metal melting furnaces are the heart of every foundry. These furnaces are used to liquefy the metal. The energy required to melt scrap metal is significantly lower than extracting metal from natural ore. So furnaces are designed specifically for each metal based on their changing properties due to melting. Arc furnaces use graphite electrodes [13] which are made up of carbon, so these furnaces cannot be used to produce low carbon stainless steel. Using different technologies in the furnace reduces the fuel consumption and heat required. The oxidation of the liquid metal and consistent flow is achieved by optimizing the furnace’s design. Conveyance of molten metal from the hotter area of the melting chamber to another chamber of the cool area without oxidation is essential. Some furnaces have employed gas feed for feeding inert gases into the conduit to induce a flow of molten metal through the conduit and simultaneously degassing the molten metal [14]. Metal melting furnaces with burners are shown in figures 3(a), (b).

2.1.1. Development in furnace based metal melting

Developing metal-melting furnaces is necessary to produce and work with metals more efficiently and achieve high-grade metal production. To reduce molten metal oxidation and ensure complete discharge of all molten metal from the melting chamber, development is the critical element to achieve it. Furnaces had trough walls shaped into a spiral form to provide a swirl of molten metal [15], but then the furnaces were developed to have a pump-induced liquid metal flow system [16]. Electric furnaces were also invented in which molten chemical salt is used to melt the metal and maintain it at the desired temperature [17]. The turbulent flow of metal can cause cross formation and gas absorption, so a closed conduit with a pump ensures a controlled transfer of the clean liquid metal [16]. Other improvements such as equipping the furnace with an arc torch [13], electric arcs for continuous melting [18], burners and multipole motor [19] as shown in figure 4, impeller tower [20], pre-heating tower [21], adding running cement to form monolithic linings in a metal furnace [22] and magnetic fields [23] are some significant developments which contributes to efficient and easy production of liquid metal.

Some improved metal melting methods were also developed where fine metal aggregates are charged into a furnace and are mechanically submerged in the forehearth furnace. Heavy scrap is fed without interference with the mechanical scrap submerger. This will establish circulation between the small body of molten metal and the larger body of the same, where uniform consistency is obtained during melting. So the readily oxidizable scrap metals which are floatable are mechanically submerged beneath the surface of a small body of molten metal out of contact with the atmosphere. The charge can also be forcibly submerged by the action of a rotating wedge blade [24]. The large body of molten metal is subjected to a higher temperature than the small body of molten metal, so this method stops the oxidation of scrap metal and uniform consistency due to the circulatory flow of molten metal [25]. A movable rotary melting chamber ensures the complete discharge of all molten metal and reduces the length of the pouring stream of the molten metal, reducing the oxidation of the metal and thus reducing metal loss from oxidation [26].

To reduce oxidation, some furnaces have an inert gas feed to induce flow [14], and some furnaces have inert gas bubble-actuated molten metal pumps with flame-resistant and heat-resistant covers [27]. These pumps help the circulation of molten metal throughout the furnace and reduce splashing, spattering, and oxidized layers in the molten metal at the surface. Some of the comparisons of the different metal melting systems are listed in table 1.
Some inventions along the way use Molten metal in a bath to melt the metal particles by mixing the metal particles into the bath. A vortex-like flow is created by the rotatable impeller, which is immersed in the molten metal. The metal particles deposited around the impeller are submerged immediately, preventing oxidation and other undesired dross [28]. The flow of molten metal can also be generated with a submergence vessel that has no moving part and does not generate a vortex. This vessel creates a downward pull that draws the molten metal into a bath [29]. The scrap metal melting process development throughout the decades are listed in figure 5.

2.1.2. Emissions from scrap metal melting
Scrap metal melting processes release polychlorinated dibenzofurans and dibenzo-p-dioxins (PCDDs, PCDFs) into the environment. A 10-ton electric furnace is used to study emissions of PCDFs and PCDDs from scrap metal melting. Ash samples can detect the presence of chlorinated dioxins and dibenzofurans. The total formation level during the scrap metal melting process depends on the organic material initially added. The feedstock used was + CaCl2, scrap metal with ‘no chlorine,’ chlorine-containing PVC plastics, and cutting oils containing chlorinated additives. PVC is one of the sources of PCDDs and PCDFs, and it was found to give the

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Figure 3. (a). Metal melting furnace (Top view) (b). Metal melting furnace (isometric view).
highest emissions in different pyrolytic processes and combustion. The amount of chlorine added during the charging process determines the formation of PCDFs and PCDDs [31].

Monometallic borohydrides and borohydride eutectic mixtures can lead to the release of hydrogen and diborane gases. Under cooling, condensation, formation of crystals, bubbling, frothing, and decomposition occur in different Eutectic compositions. The use of borohydrides can lead to uncontrolled bubbling and frothing. This can further lead to mass loss and evolved gas composition under thermolysis [32].

Noxious fumes from the furnace can be harmful to the workman, so a safety scaffold for the limited movement of the workman on the scaffold is necessary. This scaffold will remove noxious fumes and slag encrustations from the furnace wall [33].

### 2.2. Electrical arc furnace

An electric furnace uses molten chemical salt to melt the metal and maintain it at the desired temperature for pouring. The first chamber contains an upper layer of molten metal, and the second chamber with the lower layer of molten salt of greater specific gravity is used when an electric supply is passed through the electrodes in the chamber, thus heating the molten salt. A passageway connects the chambers, and a discharge spout is at its entrance end above molten metal level. The salt moves to the other chamber, which raises the molten metal level to the height of the entrance end of the spout [17].

The electrical system automatically controls the electrode level, which lifts and lowers each electrode following the electrical parameters. Electrodes are lowered in an electric arc furnace to strike an arc on the cold scrap; the electrical system automatically manages the electrode level, elevating and lowering each electrode according to the electrical parameters. The arc generates heat through radiation and current resistance to melt the scrap (through the metal). The lesser metal loss is an inherent benefit of electrical heating [1].

Almost all furnaces have a dome-shaped refractory roof with three electrodes and are three-phase AC direct arc. Monolithic materials, Bricks, or a combination of both are commonly used to line the hearth and sidewalls (as shown in figure 6). Acid refractories (silica-based), basic refractories (magnesite-based), and neutral refractories (in some situations) line the furnace sidewalls, hearth, and roof (alumina-based). All significant additions to the furnace are made through the roof by swinging the roof out of the way and charging scrap, fluxes, and carbon from loaded buckets [1].

Power sources such as Solid-state inverters are used in coreless induction melting under medium-frequency. Cupola furnace, arc furnace, induction melting, and resistance heated furnace are different techniques used majorly. The direct way to employ melting is through joule heating. The amount of power required for this process is 550KW, but it is significantly reduced to 440KW when the specific methods are followed. Oxy-fuel burners, secondary refining, and Water-cooled panels are equipped. The material’s resistivity converts the electrical energy into heat which melts the charge inside the furnace. The voltage fed inverter, a series inverter, and current fed inverter, a parallel inverter, are the two types of melts used [34].

Electric furnaces’ inherent ability to provide precise molten metal temperatures and metal chemistry indicates that they are likely to gain popularity, especially as the melting industry faces increasing pressure to maintain and guarantee quality while maximizing profitability [34].
| Furnace system          | Raw material                      | Pre-heating | Gas absorption                              | References |
|-------------------------|-----------------------------------|-------------|---------------------------------------------|------------|
| Submerged melting       | Scrap metal pieces                | Pre-heating is performed | Chances of gas absorption                   | [15]       |
| Electric furnace        | Metal with molten chemical salt   | No pre-heating is performed | Chances of gas absorption                   | [17]       |
| Burner                  | Large and small metal fragments   | Pre-heating is performed | Fewer Chances of gas absorption             | [19]       |
| Pre-heating tower       | Large and small metal fragments   | Pre-heating is performed | Significantly fewer chances of gas absorption | [21]       |
| Degassing               | Large and small metal fragments   | No data     | Significantly fewer chances of gas absorption | [14]       |
| Magnetic field device   | Non-ferrous metal pieces          | No pre-heating is performed | Fewer Chances of gas absorption             | [23]       |

Table 1. Comparison of different metal melting furnace systems.
2.3. Electron beam melting

CAD was used to construct complicated, three-dimensional components utilizing EBM of different (Ti-6Al-4V) materials. The dimensions and dislocation substructures of solid, fully dense Ti-6Al-4V products produced by additive layer manufacturing with EBM had acicular alpha-phase structures whose dimensions and dislocation substructures could be changed by varying build parameters, resulting in cooling rate variations. Porous constructs with densities ranging from 94 to 64 percent (2.8g cm\(^{-3}\)) were produced due to changes in the melt scan rate and beam current, but these porous products were not evenly sintered, resulting in unconsolidated portions with limited integrity.

Unlike selective laser melting (SLM), which can be utilized on metals, polymers, and ceramics, the electron beam’s application field is limited to metallic components due to the requirement for electric conductivity. On the other hand, the electron beam operates in a vacuum, can travel at extremely high speeds, and has considerable beam power. SEBM is particularly well suited to the processing of high-performance alloys due to these characteristics [35].

Complex, reticulated mesh arrays with precise geometrical lattices and densities suitable for bone were created (1.9g cm\(^{-3}\)). These arrays of mesh are combined to make prototypes to produce functional products. The related structures are discovered as alpha1-phase martensite or alpha1-phase martensite combinations, with the arrays of a mesh having maximum hardinesses compared to the solid components. As previously stated,
variations in EBM construction parameters led to unconsolidated zones, so maintaining optimal conditions was crucial.

Inclusions of gas are inside the precursor, and the atomized powders have been included in optimized constructions and recycled powder. These bubbles can be reduced or eliminated by HIPing. Al content was reduced by 10%–15% in optimized builds, although there was no proof of mixture alterations in powders that are reused 40 times of maximum [36]. As a result, an in situ system for detecting anomalies that arise throughout the process is particularly desirable. An infrared camera is used to image the entire build area after each completed layer to ensure layer quality. It compares photos obtained during the sample construction with metallographic images collected from various cross-sections of final parts to validate the thermal imaging results [37].

The part’s orientation has an impact on its quality as well. In order to avoid deformation due to inefficient energy dissipation, the supporting structure must be used. The supporting structures must be able to conduct energy and be easily removed once the section is completed. Several variables with various origins determine the amount of powder removed [38].

Destructive analysis can also examine the build log and find problem notations of particular build locations as part of the strategy. EBM manufacturing of products using powders offers a large amount of waste reduction through recycling of powder, as well as the potential to build components based on a specific field from Computer-Aided Design systems, particularly shapes of complexes such as mesh arrays and functionally graded, 3D components in contrast to machining wrought or cast precursors [36].

2.3.1. Experimental setup for EBM

Electrons moved with a potential of 60 kV and concentrated using lenses before scanning by an embedded CAD program in the EBM system. They are scanned electromagnetically. The concentrated beam is scanned several times at a scan rate of more than 100 ms s⁻¹ with a high beam current to warm the powder bed. The beam current is lowered to 5 to 10 mm, and the melt scan speed. The beam scans x-y, resulting in melt zones proportional to the diameter of the beam and scan spacing in the final melt scan. During the melt scan, just the layer areas indicated in the software are melted. In the system, as shown in figure 7, the powders are fed from cassettes using gravity, and they rake the build table. As each successive layer of the desired product is created, they get lowered.

Matching the direction of build, which is in the direction of the z-axis relative to the x-y scanning of the layers of powder. Particle sizes of powders lie between 10 to 60 microns, having 40 microns being the nominal size. The system functions in the vacuum of 104 Torr, just like any other electron beam system. A helium gas used at the building site increases the pressure, enhancing the conduction of heat and cooling of the component.
The system vacuum is replaced in the SLM by pure Ar or N2, which offers effective conduction of heat and cooling of the component. They also protect the system from oxidation. While nitrogen's thermal conductivity is higher than argon, most materials have little change in SLM component microstructures, even though build cooling is routinely faster for SLM than EBM.

2.4. Selective laser melting

SLM is additive manufacturing that applies powder-based methodology, and they form parts one by one as a layer. Every individual laser melted track makes the product more robust and complex. The different types of machines are used to determine the parameters that affect the material properties and obtain different characteristics for different functional uses. The absorbed energy reheats the previously created track or substrate, and the energy is then carried in the form of heat further through the substrate, it causes the powder particles to sinter/melt [36]. Freeform fabrication of complex 3D metal compounds can be produced through metal powders using laser melting. Rapid thermal cycles occur at the irradiated spots due to the heating and cooling of the metal to reach the ambient temperature. This cycle occurs within a few tenths of a millisecond. The upper layer has higher maximum temperatures, and the conductivity is lower in the first consolidated layer than in the steel base plate. There is a rise in the first steady-state temperature if the number of added layers increases [39].

Powders used in the selective laser melting are pre-heated, as shown in figure 8, increasing relative density. The Al12Si powder is used with SiC and TiN as reinforcement powders to contribute 10% volume. When Al12Si is reinforced with SiC, SiC tends to break down during the build process. At higher energy densities, this effect increases. When Al12Si is reinforced with TiN, it creates parts with higher energy density and does not break down at higher energy densities. TiN increases the young's modulus, yield strength, and hardness, but ductility is decreased. This is a significant issue in high-density conditions [40].

The volume of melt produced from the material decreases as the hatch gap decreases. The effect of previously processed material acting as a heat sink for laser energy increases as the hatch distance is reduced. Compared to loose powders, re-scanned strong metal consumes minor incident laser energy. Because of these two effects, the first laser scan melts more material than subsequent scans, implying that the first scan is often the largest when the hatch distance is small [36]. Finite difference methods and finite elements can obtain numerical modeling. Argon or Nitrogen (N2) is usually added under overpressure conditions in the chamber to prevent oxidation [41].

The item is built with additive procedures, which entail creating solid material from layers of powder to appropriate shapes from profiles created with software, and other ways. Because this method does not require fixtures or tooling, it can save money and time. Ti-6Al-4V ELI specimens made with EBM or LBM systems had suitable microstructure and good properties. The specimens are found to have the same grindability as cast and wrought Ti-6Al-4V specimens [42].

AM meets Green manufacturing's development needs. Compared to traditional subtractive manufacturing techniques like cutting and milling, AM has a high utilization rate and can attain one of the essential goals of green manufacturing: resource conservation [43].
Machine learning (ML) has proved an efficient method for performing complex pattern recognition and regression analysis without explicitly developing and solving the underlying physical models. The neural network is a highly used machine learning algorithm because of its large datasets, high computing power, and advanced algorithm architecture [44].

2.4.1. Experimental setup
The SLM experiments were done using a 3D Systems, Inc. Sinterstation® Pro DM125 SLM System. A fiber laser with 200 W and 35 m laser beam diameter at the powder bed powers the System. An automated spreading system, a safety system of inert gas, and a pre-heating system of powder bed are also included in the SLM unit, as shown in figure 9. A CAD-driven spinning mirror system scans the laser beam and focuses it onto the powder bed. The powder layers are formed onto the build platform by a recoater operated mechanically, like the rake system in the EBM. The powder is given from a container that consists of a supply, and any powder left is collected and recycled [45]. The different lasers used for SLM technology are Yb-fiber laser and CO2 laser for heating. The experiment is done and observed by varying the thickness of the layer between 30–60 μm, point distance between 50–75 μm, exposure time between 50–250 μm, laser power between 125–200 W [41].

2.4.2. Developments in SLM
Over the last 15 years, layer manufacturing has progressed from:

(a) the initial stage had the development of powder, liquid, or technologies of solid-based for visualization of prototype

(b) Developments and an expanded range of materials that led to functional prototyping, initially primarily of products made of plastics

(c) now it have changed to the position of rapid manufacturing (RM) and developed to include metal parts. The primary issue is controlling melt pool behavior, which is more difficult for standard alloys with narrow melting temperature ranges.

Thermal conductivity in the melted material powder bed is believed to differ as porosity changes in the temperature measurement. For observations to be simulated, compare expected and observed track masses, and approximate total melt time and melt length to diameter (L/D) ratios, the finite element model was used [46].

The laser surface remelting process can change the original metal’s properties by changing the metal’s microstructure during melting. Micro-hardness tests are done to identify the change in the strength of the metal. The cross-sections of the remelted surface are analyzed using SEM. The microstructure of the re-solidified region is refined compared to the unmelted specimen, which has a dendritic structure. These refined microstructures have different zones such as perpendicular, cellular, and dendritically parallel to the laser beam direction [47].

Metal Matrix Nanocomposites (MMNCs) have low cost, high quality, and can be fabricated by SLM. These MMNCs are used in aerospace, automobile, biomedical and electronics industries, etc. The main issue of
MMNCs production arises due to the limited wettability of the matrix alloy and the tendency to form into groups (agglomerate) for the nanoparticles. Powder material with added reinforcement changes physical properties, and these properties can depend upon size and interface between matrix, etc [48].

Metal Matrix Diamond Composite has high strength comparatively with resin, ceramic, and metal types. Defects like micro-cracks are found due to the melting rapidly and metal materials condensation. SLM will produce metallurgical bonding between metal matrix and diamond surface. The laser beam skipped the diamond particles, which is the main problem in this method. The defects are reduced using an online recognition system to identify the particles [49].

Through SLM, surface roughness, waviness, tensile strength, and dimensional accuracy of fabricated parts are affected by laser power and can be adjusted appropriately. Multi-gene genetic programming (MGGP), an artificial intelligence technique that automatically generates expressions between process parameters, can be used. Some scientists have produced new materials for SLM, such as nickel-chrome, stainless steel, cobalt chrome, and titanium alloy. Modifying the laser power and finding the ideal value may reduce power consumption and provide a better environment. The method of Taguchi’s with a differential algorithm, cuckoo search algorithm, and many other methods helps us increase the productivity of the manufacturing process. The ensemble-based MGGP method aids in the prediction of waviness and surface roughness in SLM-fabricated prototypes. Using the stepwise regression method, they have combined the genes evolved from the Ensemble MGGP framework. The conclusions for the prediction of waviness and surface roughness are found based on the four metrics of statistics:

1. Coefficient of determination
2. mean absolute percentage error (MAPE)
3. relative error
4. RMS.

The output values for surface roughness and waviness are computed by varying the values of inputs in sequence (varying one input while keeping the various inputs constant at their mean values). With increasing laser strength, surface roughness and waviness decrease [50].

As shown in figure 10, few parameters could affect the final product’s quality if they are not maintained at an optimized level. To summarise the effects of the processing parameters, and engineering parameter known as volumetric laser energy density is widely used (E) [51],

\[ E = \frac{P}{vht} \]
2.4.3. Problems faced in SLM
The shape and size of the pool of melt, the rate of cooling, and the reactions of transformation in the melt zone affected by heat are all affected by the resulting fluid flow and heat transfer and the presence of secondary phases. Balling, porosity, residual stresses, hot tearing, and fractures are all common quality problems that may occur during SLM. Because of the lower laser energy density ($P/v$), the melt viscosity is higher, resulting in an uneven and unsmooth surface and the porosity, un-molten particles, and a soft surface finish. The residual stress in the material increases when there is a substantial change in a temperature gradient, and these deformations may cause cracks and internal damages in SLM manufactured products.

When the thermal behavior of the 3D printing process is studied, most of the defects occur due to improper study of thermal behavior. At low scan speed, instability zones occur in the form of distortions and irregularities. At high speed, Balling effect occurs where the tracks are discontinuous and shaped like a ball [45]. Mechanical properties of SLM and temperature field should be predicted with more accuracy to avoid defects like balling, crack of parts, porosity, loss of alloying elements, and oxide inclusion [48].

Heat source models, analytical temperature models are worked out using three-dimensional differential equations with different methodologies of heat conduction [53].

The change in the alpha phase to beta phase causes a sudden change of thermal physical properties. 3D finite element analysis is used to define the simulation for the selective laser sintering process by considering the specific heat and thermal conductivity. From the experiment, it has been found that strengthening the LED by developing the power from the laser is a more efficient way than reducing the speed of the scan. The maximum temperature at each spot of laser location results in a decrease with increasing distance moving [54].

Capabilities of production systems at the present limit the physical element of intelligent factories. As a result, AM is one of the most important aspects of Industry 4.0. Because of the necessity for mass customization in Industry 4.0, non-traditional production methods must be developed. As a result of its ability to build complicated items with advanced features (new materials, forms), AM may become a powerful technology for creating intricate and delicate products. It may offer a method to replace traditional manufacturing procedures because it is a developing technology that allows faster, accurate, and strengthened intricate products. New materials, including innovative materials and metallic components, are being developed for AM to attain the desired features [45, 52]. Table 2 mentions some of the parameters of emerging melting technologies.

2.5. Simulation software
The finite difference (FD), finite elements (FE), and the finite volume method (FVM), which was created as a specific formulation of finite difference, are the most widely used numerical techniques. Depending on the problem to be solved, each strategy has its own set of benefits and drawbacks. The finite volume method is one of the most versatile and adaptable methods for solving fluid dynamics issues [60].

1. The equations of conservation for 2D laminar flow with constant physical constraints in cartesian coordinates parameters and adequate boundary conditions for this problem are in the appendix [conservation equations, Momentum equations, energy equation]. These are set of 4 non-linear, coupled partial differential equations, solved in an iterative manner using Patankar’s control volume-based finite-difference approach. A fully implicit formulation was adopted for the time-dependent variables, and the combined convection/diffusion coefficients were calculated using Patankar’s power law method. The SIMPLE technique is used to solve the continuity equations and momentum equations to derive the velocity field. The algebraic discretization equations were iteratively solved using a line-by-line solver based on the TDMA [Tridiagonal Matrix] [3].

2. The numerical solution of the two-dimensional heat flow equation with Dirichlet boundary conditions was obtained using the finite volume numerical grid technique for steady-state heat flow problems. The TDMA solver is used for solving algebraic equations, and the results generated by this method are all in good agreement with the precise solutions under examination. Compared to other expensive strategies, this methodology is effective, reliable, exact, and easier to implement in FORTRAN programming [60].

3. Some studies were obliged to adopt numerical approaches due to difficulties with analytical solutions. The number of dimensions in numeric models is essential because it influences the speed with which specific software (such as ANSYS) can calculate them and how similar they are to real-world models. Finite element and finite difference methods are the two basic approaches to numerical modeling. Artificial neural networks with deep learning are currently actively developed and applied in a variety of industries [41].

4. The current research used a 3D simulation of gallium melting in an orthogonal container to depict a schematic arrangement of the entire system, which includes moving permanent magnets beneath the container bottom. COMSOL Multiphysics software was used to simulate gallium melting in a rectangular
Table 2. Process parameters of emerging melting technologies, which influence the process.

| Types of Method       | Temperature | Power   | Energy  | Frequency | Current          | Materials melted                  | References |
|-----------------------|-------------|---------|---------|-----------|------------------|-----------------------------------|------------|
| Solar Furnaces        | 4000 °K     | 1500 Kw | 1000KWh |           | 100–120 watts    | Al, Ln, Zr                         | [55, 56]   |
| Electric Arc Melting  | 1–2.2 KW    | —       | —       | <250KHz   | —                | Al                                | [54]       |
| Microwave             | <250 deg celsius | 900W   | —       | 2.45GHz   | —                | Tin                               | [57]       |
| Electron Beam Melting | <3500 deg celsius | 100–3000 KW | —       | —         | 5–10 mA (DC)    | Steel, Ti, Zr, Nb, Ta, Mo          | [1, 45, 58]|
| Plasma heating        | 20,000 K    | >500 KW | 51,000KWh | —         | 712 A            | Wollastonite, Anorthite, Zircon, spinel | [1, 59]   |
cavity using the finite element method (FEM). In essence, the calculation is divided into two stages. The average electromagnetic force is taken from the electrodynamic element of the problem in the first stage. When the electromagnetic force is included in the momentum equation in the second stage, the melting issue is calculated using the volume-of-fluid approach (VOF) [61].

5. µ- ProPlAn is a tool that helps anticipate models by structuring the process of producing surrogate models and integrating them into a consistent framework for planning. FEM (Finite Element Method) is a tool for deciphering micro-level components. When we lower the size of a portion and apply load to it, we get side effects [62].

6. The temperature field in the SLM process has been modeled in a variety of methods. The three main areas of these efforts are experimentation (in situ tests using a thermocouple, IR camera, and pyrometer), numerical modeling (FEM and FVM are utilized for simulation), and analytical modeling [33].

7. The numerical model was validated by gathering experimental data from flow simulations in a container using a gallium-indium-tin alloy of low temperature. The simulation results were compared and analyzed once the container was filled with liquid metal. The flow velocity components were detected using an ultrasonic Doppler velocimeter [61].

3. Artificial intelligence models and their significance in metal melting

Artificial intelligence can be explained as the capability of a computer, a computer with a computer infrastructure or computer control, to execute the tasks related to higher cognitive processes like making sense of the data, interpreting, acquiring knowledge from previous experiences, and generalization. Several researchers have introduced artificial intelligence methods in metal melting processes for the past fifteen years. The AI methods are used to identify, model, predict, optimize, and control complex systems when one or more than one parameter influences the processes. Some of the uses of AI are as follows:

1. For the quality assurance of foundry products
2. Monitoring and controlling the metal additive manufacturing processes
3. For modeling the crystallization process of cast aluminum alloys
4. In the classification of the melt-pool images in metal additive manufacturing processes
5. Implemented in Friction Stir Welding (FSR) with various combinations of materials
6. To develop an adaptive artificial intelligence (AI)-based gas metal arc welding (GMAW) parameter control system for Penetration and Quality Assurance in a Multi-Pass Butt Weld Application.
7. Used in developing an approach that combines the online data acquisition and efficient numerical modeling for heat exchanges in the melting furnace, and this helps in minimizing the energy consumed and the impact on the environment for melting processes of aluminum.
8. Used in identifying the In-Situ Melt Pool Signatures Indicative of Flaw Formation in a Laser Powder Bed Fusion Additive Manufacturing Process.
9. Used in the production of white cast iron, etc.

3.1. Different AI models used in metal melting processes

An artificial Neural network (ANN) is implemented to predict bead geometry for robotic Gas Metal Arc Welding (GMAW)-based rapid manufacturing. A genetic algorithm is implemented to quantify and optimize Wire Arc Additive Manufacturing (WAAM) process parameters [63].

Bayesian Classification Model is implemented for detecting the layers or sub-regions which have less quality of defects or fusion [64].

Classical ANN with one hidden layer is used to get the quality of FSW on EN AW-6082 T6 sheets type. ANN models are implemented in estimating the microhardness of AA6061 aluminum alloy [65]. ANN models are implemented in estimating the ultimate tensile strength and microhardness of AA5754 H111 aluminum plates. To establish a successful model of ANN, the model has been tested with various neurons in the hidden layer of the polyethylene material. A Wielding ANN model was developed for Al-Mg and CuZn34 to predict the tensile strength, and a relationship was established between the traverse speeds and the rotational speeds on the tensile
4. Evaluating artificial intelligence implementation

The below tables examine the various applications of artificial intelligence (AI) in the metal-casting process. The advancement of the basic concepts of the AI methods/tools covering Artificial Neural Networks (ANN), Fuzzy logic, SVM, ANN with optimization algorithms, and other methods are discussed in the below tables accordingly.

In tables 3 and 4, we have mentioned the different applications of the ANN model and fuzzy logic for metal melting processes. Artificial Neural networks (ANNs) have shown significant challenges in predicting, optimizing, controlling, monitoring, identifying, classifying, modeling, and so on in the metal melting process. Fuzzy models are based on observing that people make decisions based on inexplicit and numerical information. Fuzzy models or sets are mathematical means of representing vagueness and inexplicit information. These models can recognize, represent, manipulate, interpret, and utilize data and information, which is vague, lacks certainties, and is applied to practical problems to select the casting process. These tables present a review of the usage of ANNs in the application of metal melting processes. We discussed several vital points which must be focused on when implementing neural networks for real-world problems, and the steps to be chosen for developing such models are also described. This involves collecting data, the gathered data division and pre-processing of the available data, selecting appropriate inputs for the model, outputs, process parameters, training algorithms, training modes, choice of performance criteria for training (learning), and model validations.

The key issues are addressed as follows:

1. Generating the training or learning samples for ANN
2. Selecting the ANN type
3. Selecting the inputs and outputs for the model
4. Designing appropriate network architecture
5. Selecting appropriate training or learning algorithms for training the models
6. Selecting the number of hidden layers, neurons, activation functions, and other parameters of the network
7. Selecting appropriate optimization algorithms for different inputs and outputs are also called hybrid models

Table 3 represents the applications of the ANN algorithm in different metal melting processes. The neural network helps in predicting misruns, airlocks, and cracks accurately in most cases, and also this model helps in successfully predicting the other defects. ANN uses tuning a set of parameters known as weights to predict the relationship between the given inputs and their related outputs. These weights are linked with the connections among the neurons within the network. By altering these weights, training of the model is done. The learning algorithm helps in adjusting the weights accordingly to minimize the errors. From the below table, it can be observed that the ANN model requires a considerable amount of input data, and it is also a challenging task to select a suitable learning algorithm for this model and also explains how different learning algorithms like the backpropagation algorithm, Levenberg-Marquardt’s method are used to train multilayer perceptron (MLP). Neurons calculate the sum of the weighted inputs, and then a linear or non-linear function is applied to the resulting sum to get the output, and the neurons are ordered in layers and are combined through excessive connectivity. The NN model is used to implement the control structure of the production of white cast iron, as mentioned in table 3.

Table 4 represents the applications of the ANN model with optimization algorithms. It explains that the primary goal of optimization was to reduce the processing time of casting. These methods are introduced to assess weld quality. Table 4 presents a mechanical & microstructural feature evaluation using ANN combined...
| Artificial intelligence method | Purpose and system layout | Inputs | Outputs | References |
|-------------------------------|---------------------------|--------|--------|------------|
| Feedforward Artificial Neural network (ANN) | Used in the classification of the melt-pool image following laser power. | A set of 22,000 images of melt-pool with pixel intensities of $60 \times 60$ arrays were transformed into a single array of $1 \times 3600$ array | Estimated output | [64] |
| | REL is the activation function used in this model | | | |
| | Ad Delta is the gradient-based optimizer that is used in this model. | | | |
| | Researchers trained the networks by | | | |
| | (1) Changing the number of hidden layers and keeping the number of nodes fixed at each layer | | | |
| | (2) Changing the number of hidden layers and the nodes decrease as the layer number increases. | | | |
| | (6) The values such as MSE (mean squared error) and Regression Coefficient R are finally calculated and trained to get the desired outputs. | | | |
| | | | | |
| Backpropagation Artificial Neural Network | To develop an ANN-controlled robot welding system for multi-pass butt welding of 12 mm S420MC plate without root support. | Root face, Root gap, | | [63]. |
| | This system adjusts to different welding conditions like root gap, root face, and tack welds such as shape and size to get a more consistent weld outcome and weld quality. | 70% data — sent to the training phase | | |
| | Welding Process — GMAW (135) | 15% data — sent to the testing phase | | |
| | Laser sensor — Meta SLS50-v1 | 15% data — sent to evaluation data. | | |
| | Network Configuration — 2-20–202 | | | |
| | Offline supervised learning is used in this model and the Levenberg-Marquardt algorithm is used. | | | |
| | Three experiments (A, B, C) are done with differing welding conditions | | | |
| Standard Feed-forward Artificial Neural network(ANN) | Used in predicting the mechanical properties of the materials | Tool rotation speed, Weld speed. | Yield strength, Tensile strength, Hardness, Elongation, | [66] |
| Artificial Neural Network (ANN) | Used in predicting the Mild Steel/Al2O3 Nanocomposite’s microhardness. | nano-sized Al2O3 powder’s addition, Number of passes, tool traverse speed, tool rotation speed | Hardness of heat-affected zone (HAZ), Microhardness | |
| ANN and regression model | Used in modeling prediction of magnesium alloys. | transverse speed, Rotational speed and axial load | Tensile strength | |

*Table 3. ANN algorithm used in metal melting processes.*
| Artificial intelligence method | Purpose and system layout | Inputs | Outputs | References |
|-------------------------------|---------------------------|--------|---------|------------|
| ANN model with Finite Element Method (FEM) | Implemented in titanium alloy (Ti–6Al–4V). Two neural networks are used by 3 and 4 hidden layers. | Temperature, Strain rate, Plastic strain | Microhardness, microstructure | [66] |
| ANN model | Implemented in aluminum surface composites like AA6082. | groove width, Rotational speed, ceramic particle type, traverse speed | Wear rate | [66] |
| ANN model | (a) Used in attaining the AA1100 aluminum’s joints tensile strength (b) Levenberg–Marquardt (LM) and Brayden Fletcher Goldfarb Shannon Quasi-Newton (BFGS QN) training algorithms are used to establish a relationship between tensile strength and process parameters | Welding speed, Tool rotation speed, diameter of the pin and diameter of the shoulder | Tensile strength | [66] |
| ANN model | (a) Implemented for the magnesium alloys modeling. (b) Compared to the regression model, the ANN model is better because it fits the experimental data better. (c) The materials used are AZ61 and AA6061. | Translational speed, Rotational speed, tool geometry, axial load | Tensile strength | [66] |
| ANN model | (a) Used for calculating the mechanical features of FSW of AA6351–AA5083 dissimilar aluminum alloys. | Rotational speed, the profile of Tool pin, Welding speed, and axial force | Tensile strength | [66] |
| ANN model | (a) Used in estimating the FSW parameters for an aluminum alloy of type 7075-T6 | The rotational speed of the tool, axial force, welding speed, shoulder diameter, tool hardness, a diameter of the pin | Tensile strength, Yield strength, hardness of welding zone, and notch tensile strength | [66] |
| ANN model | (b) Backpropagation algorithm is used in this model, and different transfer functions are tested. (a) This model used the Finite Element Method (FEM). (b) Used for aluminum alloys of type AA6082-T6 and AA7075-T6. | Temperature, Strain rate, Plastic strain | Microstructure | [66] |
| ANN model | Used in predicting the susceptibility of intergranular corrosion of the processed specimens of FSR by using 18 samples on AA5083. | Shoulder diameter, translational speed, and Rotational speed. | Intergranular corrosion susceptibility | [66] |
| ANN model | This model used the FEM method It is used for titanium alloy of type Ti–6Al–4V. It is used for Modelling Prediction of the above alloy | Temperature, Strain rate, Plastic strain. | Microstructure, microhardness | [66] |
| ANN model | (a) This model is used in estimating the mechanical behavior of the thermoplastics welding joints. | Tool plunge rate, preheating time, Tool rotation speed, | Torques, temperatures, shear resistance, temperatures, Plunging forces | [66], |
| ANN model | (a) Developed and tested many ANN models by changing the number of neurons, layers, and transfer functions for | Type of material, tool rotation speed, tool traverse speed, | Tensile strength | [66] |
| Artificial intelligence method                  | Purpose and system layout                                                                                                                                                                                                 | Inputs                                                                                                                                                                                                 | Outputs                                                                                                                                                                                                 | References |
|-----------------------------------------------|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|------------|
| ANN model                                     | The model was trained by taking inputs from the created thermal model, and the outputs are simulated and compared with the experimental data for thick 7449 aluminum alloy. It is used for Modelling Prediction. | CSRR and parameters a and b of contact gap conductance                                                                                                                                              | CSRR and parameters a and b of contact gap conductance                                                                                                                                               | [66]       |
| Feed-forward backpropagation neural network   | (a) Used in predicting the number of alloying additives required to get the wanted white cast iron’s chemical composition. (b) Levenberg-Marquardt algorithm was used in this model. (c) 80% of data is used in the training phase, 10% data is used for validation, 10% data is used for testing phase. (d) Several models like this are trained with one input layer of 12 inputs, one output layer with four outputs, and one hidden layer with 12, 14, 15, 16, 18 neurons. Moreover, the mean squared error (MSE) is calculated for each model and tested by giving anonymous data for the alloying additives' mean and maximum errors. | The inputs are: a) 2.5 tons of molten metal in a furnace, b) chemical composition of 5 tons of steel waste c) Final chemical composition of molten metal                                                                                                                                                                                                 | Amount of alloying additives that are added in the alloying process, carburizing agent (kg), Farce (kg), Fen (kg) and Fez (kg). Predicting the additives in the alloy                                                                 | [67]       |
| AI method                        | Purpose and system layout                                                                 | Inputs                                                                 | Outputs                                                                                                           | References |
|---------------------------------|-------------------------------------------------------------------------------------------|----------------------------------------------------------------------|-------------------------------------------------------------------------------------------------------------------|------------|
| ANN model and fuzzy logic controller | In the Fuzzy logic model, seven membership functions are used                              | Tool type, tool probe diameter, and shoulder fat surfaces            | The cross-sectional area of weld, Weld strength, weld’s average grain size, Synod grain size                       | [66]       |
| NSGA-II based ANN model         | (a) A multi-objective optimization has been implemented in this model                      | Profile of Pin tool angle, weld speed, rotational speed               | Vertical force, Horizontal force size of the grain, temperature, tensile strength, joint thickness, hardness and elongation | [66]       |
|                                 | (b) It is used for AA1100 material                                                        |                                                                      |                                                                                                                  |            |
|                                 | (c) It is used for the Optimization modeling technique                                     |                                                                      |                                                                                                                  |            |
| ANN with GA model               | (a) This model is used for AA6061-T6 material                                             | Penetration depth, Rotational speed, dwell time                      | Maximum tensile force, process time, and plunging load                                                          | [66]       |
|                                 | (b) The ANN parameters were optimized and became robots by using the genetic algorithm (GA) and provided better results compared to the conventional ANN model |                                                                      |                                                                                                                  |            |
|                                 | (c) This model is used for the Optimization modeling technique                             |                                                                      |                                                                                                                  |            |
|                                 | (d) This model is a hybrid-heuristic model                                                 |                                                                      |                                                                                                                  |            |
| ANN with GA model               | (a) This model is used for AA5083-O-AA6063-T6 dissimilar aluminum alloys                  | Rotational speed of the tool, welding speed, diameter of the pin, and shoulder diameter | Microhardness, Tensile strength, and size of the grain                                                             | [66]       |
|                                 | (b) This model is used for modeling, prediction, and optimization                          |                                                                      |                                                                                                                  |            |
|                                 | (c) This model is a hybrid-heuristic model                                                 |                                                                      |                                                                                                                  |            |
| NSGA-II based ANN model         | (a) This model is used for A356 cast alloy                                                | Traverse speed, Rotational speed,                                   | Size of Silicon particle, axial force, hardness, and tensile strength                                             | [66]       |
|                                 | (b) Used for optimizing the mechanical and microstructural features of composites like SiC, TiC, ZrO2, and B4C |                                                                      |                                                                                                                  |            |
|                                 | (c) This model is used for the Optimization modeling technique                             |                                                                      |                                                                                                                  |            |
|                                 | (d) This model is a hybrid-heuristic model                                                 |                                                                      |                                                                                                                  |            |
| ANN with particle swarm optimization (PSO) model | (a) This model is used for aluminum alloys of the types AA5083-O and AA5083-O        | Traverse speed, Rotational speed,                                   | Tensile shear force and hardness                                                                                   | [66]       |
|                                 | (b) This model is used for modeling, prediction, and optimization                          |                                                                      |                                                                                                                  |            |
|                                 | (c) Implemented for testing the relationships between the mechanical features and welding parameters |                                                                      |                                                                                                                  |            |
| Grey Relational Analysis (GRA) based ANN model | (a) This model is used for AA6082-T6 material                                           | Tools, tool rotation, welding speed, and tilt angle                 | Tensile strength and impact strength                                                                             | [66]       |
|                                 | (b) This model is used for modeling, prediction, and optimization                          |                                                                      |                                                                                                                  |            |
|                                 | (a) This model is used for AA1100 material                                                | Tool parameters                                                     |                                                                                                                  | [66]       |
| AI method | Purpose and system layout | Inputs | Outputs | References |
|-----------|---------------------------|--------|---------|------------|
| ANN with PSO, GA, DE(differential evolution) model | (b) This model is used for modeling, prediction, and optimization | Ultimate tensile strength, yield stress, bending angle, percentage of elongation, and hardness | [66]. |
| ANN with GA, a DE model | (a) It is used for AA1100 material | Plunge depth, welding speed, the rotational speed of the tool, tool geometry, diameter of the pin, shoulder diameter, pin length of the tool, and dwell time | Ultimate tensile strength, yield stress, bending angle, percentage of elongation, and hardness | [66]. |
| ANN with GA model | (b) This model is used for modeling, prediction, and optimization | Ultimate tensile strength, yield stress, bending angle, percentage of elongation, and hardness | [66]. |
| ANN with GA model | (a) This model is used for AA1080 material | The rotational speed of the tool, welding speed | Microhardness, Tensile strength, and corrosion resistance | [66]. |
| ANN with Gray Wolf Optimization Algorithm (GWOA) model | | Rotating velocity, the interlayer thickness of Zn, welding speed, and ultrasound power | Tensile shear load | [66]. |
| ANN with adaptive neuro-fuzzy inference system (ANFIS) model | (b) This model is used for modeling, prediction, and optimization | Spindle speed, welding speed, plunge force, and empirical force | Ultimate tensile strength | [66]. |
| ANN with adaptive neuro-fuzzy inference system (ANFIS) model | (a) This model is used for AA-2219-T87 panels | | | |
| ANN with GA and particle swarm optimization (PSO) and | (b) This model is used for the Optimization modeling technique. | Green shear strength, green compression strength, permeability, the moisture percentage composition of the melting, and charge conditions. | Defects formed due to mild sand system | [67]. |
| ANN with QPSO algorithm(improved PSO algorithm) | (a) Used to predict casting defects like cracks, microlites, etc, | (b) Used for the green sand mild system. | The input values are optimized, and the element’s time of filling, time of solidification, and oxide ratio are reduced | [67]. |
| ANN with QPSO algorithm(improved PSO algorithm) | (c) GA and PSO are used in optimizing the green sand mild system. | (d) In this model, relationships are formed between process parameters and responses like permeability. | | |
| ANN with QPSO algorithm(improved PSO algorithm) | (a) This model is used for defects reduction in casting, and thus the quality of casting is improved b) PSO algorithm helps optimize the elements like time of filling, time of solidification, and oxide ratio. | riser diameter, pouring speed, pouring temperatures, riser position, and pouring diameter | | |
| AI method                        | Purpose and system layout                                                                 | Inputs                                                                 | Outputs                                                                 | References |
|---------------------------------|------------------------------------------------------------------------------------------|------------------------------------------------------------------------|------------------------------------------------------------------------|------------|
| Multilayer Perceptron (MLP) with feed-forward neural networks (MLP) | (a) Basically, three dependent layers are involved. They are input, hidden, and output layers. | Laser power, Scanning speed, Hatch speed | Ra value which is the surface quality of 316L stainless steel          | [68]       |
|                                 | The sigmoid activation function used for the hidden layer is                                  |                                                                        |                                                                       |            |
|                                 | $f(x) = \frac{1}{1+\exp\{-b_1^h + \sum w^h_i x_i\}}$                                    |                                                                        |                                                                       |            |
|                                 | Where $b_1^h$ is the bias of every neuron in the hidden layer, $w^h_i$ is the weight of the jet neuron of the hidden layer with its input, and $x_i$ is the input parameter. |                                                                        |                                                                       |            |
|                                 | The function of the output layer is a linear function that is                               |                                                                        |                                                                       |            |
|                                 | $f(x) = b_s + \sum w^o_i x_i$ where $b_s$ is the bias of the neurons of the output layer and $w^o_i$ is the weight of jet neuron of the hidden layer |                                                                        |                                                                       |            |
|                                 | The input and output are normalized to the range $[0,1]$.                                   |                                                                        |                                                                       |            |
|                                 | 80% of the data is used for training, and the remaining 20% is used for the testing phase.  |                                                                        |                                                                       |            |
|                                 | The four training parameters are learning rate ($l$), moment constant ($c$), training epochs ($e$), and several hidden neurons ($n$). The ranges of these parameters are: |                                                                        |                                                                       |            |
|                                 | 1. $l$: 0.01–0.05                                                                          |                                                                        |                                                                       |            |
|                                 | 2. $c$: 0.1–0.9                                                                            |                                                                        |                                                                       |            |
|                                 | 3. $e$: 2000–3000                                                                           |                                                                        |                                                                       |            |
|                                 | 4. $n$: 2–6                                                                               |                                                                        |                                                                       |            |
|                                 | A backpropagation algorithm is used.                                                        |                                                                        |                                                                       |            |
| Adaptive Neuro-Fuzzy Inference System (ANFIS) | A simplified ANFIS figure shows that the first layer is the input, where three nodes represent the selected parameters of the SLM process. In the second layer, the inputs are mapped into linguistic variables (low, medium, high) using some membership function (triangular, trapezoidal, bell-shaped, and Gaussian). | Laser power, Scanning speed, Hatch speed | firing strengths ($f_s$) of 316L stainless steel | [68]       |
|                                 | The $f_s$ values are normalized in the next step by computing the ratio between the $f_s$ at each node and the total sum of all firing strengths. After these steps, the variables are defuzzied, and a fixed node ($R$) sums the outputs of all incoming signals to calculate the overall output of the model. |                                                                        |                                                                       |            |
|                                 | The fuzzy C-means clustering (FCM) technique was selected for generating the fuzzy inference reasoning system. The learning process of the ANFIS is carried out by a hybrid algorithm that combines least squares and back-propagation. |                                                                        |                                                                       |            |
| Adaptive neuro-fuzzy inference system (ANFIS) | (a) Used in studying the parameters of the die casting which affect the formation of pores in pressure die castings of the type AlSi9Cu3 b) Used for high-process casting (HPDC) process | The temperature of the metal, the temperature of the die, velocity of the piston in the low phase, gate velocity of the die, and solidification pressure | Porosity elements | [67]       |
A hybrid GA-ANN method is proposed to forecast optimal tensile strength, microhardness, and grain size values.

When optimization methods are compared with classical, a Mamdani type of controller and seven different triangle type of membership functions are built using the fuzzy logic to get the outputs mentioned in the table. ANN and ANFIS (adaptive fuzzy inference system) are used to estimate the ultimate tensile strength of aluminum alloys. The process of two models of ANN combined with genetic algorithm (GA) and particle swarm optimization (PSO), used to optimize the green sand mild system, is mentioned in the table. So, this table describes different methods which are ultimately used for process parameter optimization.

SVM model creates a classification hyperplane as a decision surface to increase the positive and negative support-vector margin. It is based on statistical learning theory. In pattern classification, it provides a unique generalization performance. From the table below, we can say that SVR models show a considerable level of success in predicting alloying additives. They reduce risk as much as possible.

However, the ANN model has shown better results than the support vector regression model in the training and testing phases. Table 7 details a comprehensive review of the Support Vector Machine technique, and figure 11 explains the SVM implementation in the metal melting processes. Figure 12 compares the loss functions RMSE between SVM and ANN. RMSE was the only loss function that was used throughout the research conducted for metal melting processes.

The mentioned hybrid WNN model includes the capability of both wavelets and neural networks to capture non-stationary nonlinear parameters that are embedded in financial time series. The WNN-based algorithm is utilized for predicting the yield spreads. The K-nearest neighbor (KNN) algorithm is used to optimize the parameters, and it is applied in the cases where we need to classify the individual data, which encompasses the majority of the nearest neighbor. The NSGA-II and ABC algorithms are used to optimize the output values of the model. Moreover, the KNN has shown higher accuracy than other models in table 4 (see table 6). Table 6 shows a selective description of the AI models used in metal melting processes.

The visualization of the process of heating and melting metal in arc discharge with a non-consumable electrode method showed that non-uniform temperature distribution on the surface occurs in the heating spot of the welding arc with a non-consumable electrode burning in argon and that under non-steady burning conditions, and later they form on the surface of the melt. For the CNN model, the semi-supervised approach was compared against the fully supervised approach, and it was seen that the semi-supervised approach outperformed the fully supervised approach during both regression and classification.

Therefore, the algorithm used for an experiment can be depicted by the algorithm’s criteria. In table 7, how the algorithm works and if it is suitable for the experiment performed can be observed. Table 7 details the different algorithms, and their criteria. For instance, ANN can be concluded that this method was more effective than the conventional methods.

Table 8 details the different algorithms and their criteria. For instance, ANN can be concluded that this method was more effective than the conventional methods.

There is a Parameter selection process involved. The algorithm is used to find the parameters from the datasets, which it includes. Atomic Absorption spectroscopy algorithm is used to find which is efficient in cobalt and nickel by two using.

Two different methods are included with different samples. A cyber-physical production system is used for quality prediction bodybuilder, data pre-processing and exploring.

In table 9, the data findings are attained from the AI techniques implemented in the metal melting process. These findings show the accuracy of different AI models and present which AI model is chosen for which metal.

From the table, it can be said that AI techniques seem to present a functional method for optimization of parameters and mechanical properties prediction such as tensile strength, elongation, etc. The average error was approximately 5% for applied ANN techniques on the prediction of FSW parameters. The GA techniques with Fuzzy Logic have shown better accuracy than the classic fuzzy logic model. Metaheuristics algorithms have shown better accuracy than classic ANN optimization models with methods like backpropagation.

4.1. Case studies and discussions: developments in the industrial application

4.1.1. AI methods implemented for materials and their efficiency

For AA5754 H111 aluminum plates, the outputs predicted by the first ANN model are taken as the inputs for the second ANN model, and these 2 ANN models are implemented for modeling prediction, and the accuracy rate was 96%. For AA1100 aluminum, the ANN model was used for modeling prediction, and the accuracy rate was 99%. However, the BFGS QN technique has shown better results and provided closer estimation results to the experimental data than the LM technique. Fuzzy logic and ANN are used to create a prediction tool to model every FSW feature’s relationships with the system’s outputs. A fuzzy logic controller is a prediction tool developed using seven membership functions. However, a prediction tool with fuzzy logic has shown better
Table 5. Support vector machine cases.

| Artificial Intelligence method | Purpose and system layout | Inputs | Outputs | References |
|--------------------------------|---------------------------|--------|---------|------------|
| Support Vector Machine (SVM)   | It is applied to predict the mechanical property of FSW process of 6mm thick welded joint AA6061. (a) It is used for magnesium alloy of the type AZ31 (b) Both the SVM and ANN structures are used in this model (c) This ML technique is used for predictive modeling technique | Measurement data and Tool parameters | Tensile strength | [66] |
| Support Vector Machine (SVM) and ANN | (a) It is used for AA1100 material (b) Both the SVM and ANN structures are used in this model (c) This ML technique is used for predictive modeling technique | Processing time, Rotational speed, welding speed, the ratio of rotational speed to welding speed | Vertical force | [66] |
| Support Vector Regression (SVR) | (a) Used in predicting the amount of alloying additives required to get the wanted white cast iron’s chemical composition. (b) 4 SVR models were developed, and each predicted the quantity of 1 alloying additive. (c) RBF kernel function is implemented in this model. (d) The elements C, mean squared error is calculated in the training phase and finally tested by giving anonymous data where mean and maximum errors are calculated for the alloying additives. | Amount of alloying additives that are added in the alloying process. carburizing agent (kg), Farce (kg), Fen (kg) and Fez (kg) | | [67] |
results than ANN for establishing relationships. The Fuzzy with ABC and ICA model for Al alloy has shown an accuracy rate of 97% [66]. The Wavelet-Feed-Forward ANN and Wavelet-Radial basis ANN techniques are implemented for the aluminum alloy. The feed-forward neural network with multilayers has shown better results than the radial basis neural network [66]. [From table 10]

4.1.2. Comparison of both NN and SVR models

From table 8, we can say that In the process of predicting the amount of alloying additives using different Neural networks (training phase), it is observed that NN with 12(input)-16(hidden)-4(output) layers has shown the most minor mean squared error. Moreover, coming to the testing phase, the results have shown that Carburizing agent had the least Mean and Max error (0.47 and 1.97), whereas Fen had the highest Mean and Max error (3.31 and 9.42). From (table 5) [67].

In the process of predicting the number of alloying additives using four different SVM (training phase), it is observed that the highest potential for the second input set with values of 3) [ squared error as 10, 0.005, (0.38–0.47). Coming to the testing phase, the results have shown that Farce had the least Mean and Max errors (2.05 and 6.77), whereas Fez had the highest Mean and Max errors (6.65 and 14.56). From (table 10) [67].

Though both supervised learning algorithms above show slight deviations from the experimental values, it did not cause a threat to the white cast iron’s final chemical composition. This shows the higher accuracy of the NN model compared to SVR [67].
| Artificial Intelligence method                                      | Purpose and system layout                                                                 | Inputs                                                                 | Outputs                                                                 | References |
|-------------------------------------------------------------------|--------------------------------------------------------------------------------------------|------------------------------------------------------------------------|-------------------------------------------------------------------------|------------|
| Wavelet-Feed-Forward ANN and Wavelet-Radial basis ANN            | (a) The parameters of the process and properties are obtained from the wavelet package and were sent to the multilayer feed-forward ANN, and radial basis ANN and the tensile strength and yield strength of the material are estimated. | Parameters of the process, properties                                  | ultimate tensile strength and yield strength                           | [66]       |
|                                                                  | (b) These two algorithms are Hybrid methods                                                 |                                                                        |                                                                         |            |
|                                                                  | (c) It is used for aluminum alloy                                                           |                                                                        |                                                                         |            |
|                                                                  | (d) This model is used for the prediction of Signal Processing                             |                                                                        |                                                                         |            |
| Non-dominated sorting genetic algorithm (NSGA-II)                 | (a) Implemented in case of developing a thermo-mechanical model for optimizing the residual stress which is formed after the FSW process | Welding speed, Rotational speed                                          | Optimal values of residual stress                                      | [66]       |
|                                                                  | (b) It is a heuristic method                                                               |                                                                        |                                                                         |            |
|                                                                  | (c) It is used for the optimization                                                        |                                                                        |                                                                         |            |
| Artificial Bee Colony algorithm (ABC)                             | (a) Used in achieving optimal process parameters like yield strength, ultimate tensile strength, and elongation | Traverse speed of the tool, rotational speed of the tool, and axial force | Tensile Strength, Yield Strength, and elongation                        | [66]       |
|                                                                  | (b) It is a heuristic method and used for AA-6061 and AA-6351 materials                    |                                                                        |                                                                         |            |
|                                                                  | (c) It is used for the predictive optimization model                                      |                                                                        |                                                                         |            |
| K-nearest neighbor (KNN), Fuzzy K-nearest neighbor (FKNN) with ABC | (a) This model is used for AA-2219-T87 panels                                             | EFI, Feed rate, rotational speed.                                       | Welding quality                                                        | [66]       |
|                                                                  | (b) This model is used for prediction as well as for filtering and optimization            |                                                                        |                                                                         |            |
|                                                                  | (c) The ABC algorithm is used to find the optimum value of K and feature selection         |                                                                        |                                                                         |            |
### Table 7. Algorithm methods used in melting application.

| Algorithm                                                                 | Data                                                                 | Depth layer sizes, Training time, Testing time | Framework, Core Language, Interface | Advantages | Disadvantages                                                                 | References |
|---------------------------------------------------------------------------|----------------------------------------------------------------------|-----------------------------------------------|-------------------------------------|------------|-------------------------------------------------------------------------------|------------|
| Decision tree, random forest, artificial neural network (ANN), support vector machine (SVM) | Data engendering from IoT and sensor and the constructing execution systems (MES) | —                                             | C#, R, .NET framework, HBase, Spark | The ANN showed the most accurate result but had a higher model creation time. | The exchange of data can create security issues. There are also many resources needed to synch the physical and the virtual world together. There were also concerns about the standardization of the data format and the communication protocols. | [68]       |
| ANN, genetic programming, clustering, and Bayesian methods.               | Camera images and ground truth data                                   | Concealed layers: 1 or 2 layers               | —                                   | Outmatches the thresholding and also the k-means clustering. Compared to other methods, misclassification rates are three times lower. | 1h5N architecture’s performance is not better than the other available models | [69]       |
| SONY 350 and Canon 550d-18                                               | SONY 350, And Canon 550d-18–50 They were used to capture images.    | —                                             | Photoshop C3 and Lightroom          | It showed that digital photography is an effective means of measuring the brightness temperature of the anodic region of the arc in the temperature range of ~1000–3500 K with an accuracy of several degrees. | It showed that there is no standard methodology being followed through these investigations | [70]       |
| — 50 were used for the optical measurement of the temperature with brightness and pyrometry method, Adobe Photoshop C3 and Lightroom They were used for image processing. The II model from the Temporal Ensemble technique for the semi-supervised CNN model | One thousand training data points along with 500 labeled and unlabelled, and 200 test data points | Three conv and dense layers.         | —                                   | The results from the semi-supervised proposal excel to that of the supervised proposal with smaller datasets, thus allowing a reduction in the effort | The semi-supervised proposal does not allow refinement compared to the supervised method when the | [71]       |
| Algorithm | Data | Framework, Core Language, Interface | Advantages | Disadvantages | References |
|-----------|------|-------------------------------------|------------|---------------|------------|
| 3-layer cascade-forward back-propagation ANN with Levenberg–Marquardt algorithm | 1st Phase: geometrical parameters of metal trace | | | | [72]. |
| | 2nd Phase: laser DMD process parameters. | | | | |
| CNN | The liquified metal operator, device, and accident images | | | | [73]. |
| FEM, ANN, GA combined | Mechanical properties of nano-Sic particles | | | | [74]. |
| Atomic absorption spectroscopy (AAS) | Equal amounts of Co and Ni | | | | [75]. |
| Multi-layer feed-forward NN. | Fifty-four parts total were built; 48 were used to train the model and 6 to validate it. | | | | [76]. |

The average inference time was 1.4ms, with the maximum being 2.9 Ms. Total of 3 input nodes and three output nodes with the number of hidden layers ranging from 3 to 9. It showed that ANN could be used to estimate laser power, scanning speed effectively, and powder feeding rate is to attain any provided geometry.

It showed that the combined algorithm was efficient in Al matrix nano-composites to aid stir casting. It showed that any influence of Ni could be removed from consideration. The presence of Ni in the air was higher at a 2:1 ratio when compared to Co.

It showed that the same approach could be used for other RP processes.
Table 8. Algorithm methods used concerning their application.

| Algorithm | Purpose and System Layout | Inputs | Outputs | References |
|-----------|---------------------------|--------|---------|------------|
| Parameter selection process. | We will read the STL file, calculate the volume, and then go to auto-select Parameters. Here, we can select the autoselect parameters option directly and end the program. If the end-user has selected auto-select parameters, we will calculate and save the processing time under different parameter settings. We will get output as we choose the weight factors of the resulting property of service satisfied with the parameters. We can directly end the program, and else we can scan the database and find the most stable parameter setting. After that, we have to satisfy the setting. | Metallic part resulting properties | most stable parameter | [77] |
| Cyber-physical production system | This so-called cop is generally divided into three parts: Big data analysis, A detection and coordination, KPI simulation system. Here are the three major applications of extensive data analysis are listed below. Big data storage: here, we include raw sensor data such as temperature, pressure, process parameters generated from vibrations, and machines quality prediction bodybuilder: data pre-processing and exploring are done. Model repository: building a model. | Binary images, six composite sheets | Transmission of visualisation | [78] |
| carbon-fiber-reinforced thermoplastic | The Welding process is a method that consists of Vibration and monitoring some physical quantities. The significant population of manufacturing Parts performs durability and thermal tests. Due to high specific strength, high recyclability, and low ductility, these carbon-reinforced thermoplastics are getting good responses nowadays. Mainly these are getting good responses from the automotive and electronic industries. It is also believed that it is highly lightweight and mainly the new upcoming Generations will get more attracted to this. We have to install the servers to investigate the weld quality and weld technology. These signals and servers are used as artificial intelligence (AI inputs). When coming to the experimental procedure, the primary materials used are injection molding and composite sheets. These sheets of sheets are inspection of ultrasonic composite welding | Binary images, six composite sheets | inspection of ultrasonic composite welding | [79] |
Table 8. (Continued.)

| Algorithm                              | Purpose and System Layout                                                                 | Inputs                                      | Outputs                                                                                                           | References |
|----------------------------------------|-------------------------------------------------------------------------------------------|---------------------------------------------|-------------------------------------------------------------------------------------------------------------------|------------|
| density-functional theory              | A blend of orderly thickness valid hypothesis (DFT) estimations and AI strategies have a broad scope of potential applications. This examination presents a blend of efficient DFT computations and relapse strategies to forecast the dissolving temperature for single and paired mixtures. Here we receive the standard least-squares relapse (OLSR), halfway least-squares relapse (PLSR), support vector relapse (SVR), and Gaussian interaction relapse. The SVR gives the best forecast among the four sorts of relapse procedures. Incorporating actual properties figured by the DFT estimation into a set of indicator factors improves the forecast. | Impediment of the precipitant force is shown when extrapolation from preparing the dataset is required.                     | The kriging configuration tracks down the compound with the most noteworthy dissolving temperature quicker than irregular plans | [80]       |
| Atomic Absorption spectroscopy.        | The basic assumptions in this method are that there should be an equal amount of Cobalt and Nickel. | 50 Samples of urine, nickel, cobalt          | Airborne concentration                                                                                             | [81]       |
| Metal used                              | ANN | GA  | PSO | DE  | SVM | ABC | LM | Fuzzy Logic | Wavelet ANN | Other Models | Accuracy | References |
|----------------------------------------|-----|-----|-----|-----|-----|-----|----|-------------|-------------|--------------|----------|------------|
| AZ31 magnesium alloy                   |     |     |     |     |     |     |    |             |             |              | 96%      | [66]       |
| AA5754 H111 aluminium plates          | yes |     |     |     |     |     |    |             |             |              | 96%      | [66]       |
| AA1100 aluminium                       |     |     |     |     |     |     |    |             |             |              | 99%      | [66]       |
| AA6061 and AZ61 magnesium alloys       | Yes |     |     |     |     |     |    |             |             |              | 100%     | [66]       |
| AA6351–AA5083                          |     |     |     |     |     |     |    |             |             |              | 95%      | [66]       |
| AA 7075-T6                            |     |     |     |     |     |     |    |             |             |              | 0.99%    | [66]       |
| AA6082 T6                             | Yes |     |     |     |     |     |    |             |             |              | 0.72%    | [66]       |
| AA7075-T6                             | Yes |     |     |     |     |     |    |             |             |              | <50%     | [66]       |
| Polycarbonate sheets                   | Yes |     |     |     |     |     |    |             |             |              | 95%      | [66]       |
| AA7075-O and AA7075-T6                | Yes |     |     |     |     |     |    |             |             |              | 97%      | [66]       |
| Prediction tool                        | Yes | Yes |     |     |     |     |    |             |             |              | —        | [66]       |
| AA6061-T651                           |     |     |     |     |     |     |    |             |             |              | 100%     | [66]       |
| AA6061-T6 and AA6351-T6               | Yes | Yes | Yes |     |     |     |    |             |             |              | 97%      | [66]       |
| Al alloy                               |     |     |     |     |     |     |    |             |             |              |          |            |
| AA6083-O–AA6063-T6 dissimilar alloys   | Yes | Yes | Yes | Yes |     |     |    |             |             |              | 98%      | [66]       |
| for AA7075-O and AA5083-O alloys       | Yes | Yes | Yes | Yes |     |     |    |             |             |              | 98%      | [66]       |
| AA1100 material                       | Yes | Yes |     |     |     |     |    |             |             |              | 99%      | [66]       |
| AA1100 material                       |     | Yes | Yes | Yes | Yes |     |    |             |             |              | 93%      | [66]       |
| AA1080 material                       | Yes | Yes | Yes |     |     |     |    |             |             |              | 99%      | [66]       |
| AA2219 material                       | Yes | Yes | Yes |     |     |     |    |             |             |              | 99%      | [66]       |
| AA7075-T6 and AZ31BMg                 | Yes |     |     |     |     |     |    |             |             |              | 90%      | [66]       |
| AA-2219-T87 panels                    | Yes |     |     |     |     |     |    |             |             |              | 100%     | [66]       |
| Al alloy                               | Yes |     |     |     |     |     |    |             |             |              | 97%      | [66]       |
| AA-2219-T87 panels                    | Yes |     |     |     |     |     |    |             |             |              | 93%      | [66]       |
| pressure die castings of the type AlSi9Cu3 |     |     |     |     |     |     |    |             |             |              | 93%      | [67]       |
| low-pressure die-cast (LDPC) process   | Yes | Yes |     |     |     |     |    |             |             |              |          |            |
| For continuous casting process         | Yes | Yes | Yes |     |     |     |    |             |             |              |          |            |

*Table 9. Based on the observations, the model used and its accuracy for different materials.*
4.1.3. Implementation of spectral convolutional neural network (SCNN) for the metal additive manufacturing processes

For metal additive manufacturing processes, Spectral Convolutional Neural Network (SCNN) has the advantages of traditional convolutional neural networks and the extra benefit of processing data with more complex structures (or geometries) with less computational effort is implemented. Here, Graphs are used to capture the input data’s irregularity. A feature extraction tool guides the network to optimize its structure during the training process. Here, the classification accuracy was high. However, we can further improve its accuracy by using two running windows indicated as short and long-running windows (SRW and LRW, respectively). The wavelet spectrograms for SRW and LRW were formed separately and were sent as inputs for the SCNN classifier [82].

Later, an exhaustive search was performed to recognize the optimal window sizes [82]. The previous methodology is used for laser welding, and the signals are classified into four categories: contains no illumination category, conduction welding category, keyhole containing porosity category, and keyhole with no porosity category. Based on the output table, we can explain that: The diagonal elements show the percentage of the classification accuracy of the corresponding categories, whereas, in the case of the remaining boxes, the 0.0% classification accuracy shows they are predicted accurately and are not mistaken with other categories. However, the values other than 0.0% in other boxes indicate the percentage of the corresponding categories in the rows that are mistaken with other categories in the columns. The most miscategorized categories are keyholes containing porosity and keyhole with no porosity [82].

4.1.4. 10HL-DNK2 and 10HL-360NA for classification of melt-pool images

In the case of classification of images of the melt-pool, 10HL-DNK2 (NN with ten hidden layers and $k = 2$ where the number of nodes is dropped by an increase in the number of layers) showed better performance compared to 10HL-360NA (NN with ten hidden layers and the number of nodes is 360 at each layer) because when compared to the sum of pixel intensity in images of melt-pool which is a simple calculation, it handled different shapes simultaneously. This is only utilized as a classifier because of its weak performance on the LOO evaluation [64].

4.1.5. AI methods used for foundry processes

Figure 13 describes the factors affecting the defects formation in foundry processes. Figure 14 describes the primary uses of Computational intelligence. So, in order to meet the above needs from the figures, we use induction of decision trees (Cart and CBR algorithms), fuzzy logic, rough set theory, ANN (Artificial Neural Networks), and Case-based reasoning [83].

However, the limitations of using them are: It is difficult for humans to interpret neural networks. The incapability of formulating the inference rules for incapability continuity lacks prediction, even with the help of a decision tree (Cart). The incapability of creating a single model for many dependent variables for Cart regression trees. Fuzzy logic needs domain knowledge has low accuracy results, and it is incapable of making decisions in new situations [83].

4.1.6. Automated inspection of molten metal using machine learning

We can obtain the results by performing an experiment where the image sent is pre-processed, RGB formal is used to check the background segments, and vector extraction of value $x$ is operated for ANN classification. If this classification criterion is satisfied, then the decision is made, and the output is given in the ANN classification. The learning algorithms are induced by which we can know the facts of ground truth for the issued image, and the process is verified [69]. (figure 15)

4.1.7. The assistance of novel artificial intelligence in optimization of aluminium matrix nanocomposite by genetic algorithm

We can get the results by performing an experiment where the values are assigned to the initial population and calculating its fitness by elitism. By checking the termination status, we will have two options: if the criteria are satisfied, the other process is processed, GA training is stopped, BP training is performed, and we get the output.
If the criteria are not satisfied, then the process is processed again by checking the selection and new population by which we can get correct results [70]. (Figure 16)

4.1.8. Results of the experiment performed
The proposed method was compared to traditional methods like thresholding and k-means clustering, and it was concluded that this method was more effective than the conventional methods [69]. It also showed that non-uniform temperature distribution on the surface occurs in the heating spot of the welding arc with a non-consumable electrode burning in argon and that under non-steady burning conditions, the welding arc’s anode spots are present at the edge of the heating spot at the moment of formation of a molten pool, and later they form on the surface of the melt [69]. An increase in bias offset leads to increased users trying to offload to an MPs or fixed small cells, resulting in edge throughput reduction due to high load conditions. To balance this loss, the authors suggested that the density of the MPs deployed could be increase [70]. In the end, the semi-supervised
approach was compared against the fully supervised approach, and it was noted that the semi-supervised approach outperformed the fully supervised approach during both regression and classification [71]. In the second phase, reverse data processing took place to verify the results obtained from the ANN in the first phase. For training the ANN in the second phase, feature pattern vectors (FPV) were constructed by combining the DMD process parameters laser power (P), scanning speed (v), and powder feeding rate (m). It was concluded from this phase that the neural network showed high accuracy. This resulted in a successful verification of the results obtained in the first phase [72].

4.1.9. SLM in embedded sensors for self-cognitive parts
This paper tackles the challenges related to the process of embedding sensors or circuits directly to metal parts by putting forward a thermal protective layer for embedding the sensor throughout the selective laser melting (SLM). The first part contains the sensor or the circuit and has an engraved section for the same. The second part is used to complete the final shape. There are three significant steps in the SE-SLM process. It starts by printing a part according to the first SLM part design. The next stage is to remove the powders in the engraved region and place the sensor of the circuit in its place. The pre-prepared protective layer is then put on top of the engraved
region. The final stage of the process includes printing the leftover part with the second SLM design's help. It was noticed that the sensor remained safe from any thermal damage. The engraved region's temperature was able to be maintained throughout the melting process of metal powder. It was also noted that the inclusion of metal parts between the two SLM parts did not damage the mechanical properties and the microstructures. It was also examined and confirmed that the embedded circuits could communicate with the help of Bluetooth or WiFi connections. The sensor's sensing properties were also validated with the help of a thermocouple and an IC chip, respectively. The authors suggested that this communication concept could allow us to gather critical real-time data in the future, which can be particularly useful for intelligent status analysis via machine learning [75].

4.1.10. CNN based monitoring and early warning system of molten hazards
The results from image recognition are used for the proper functioning of the various subsystems, namely, the Real-time monitoring subsystem, Safety inspection subsystem, Safety early warning subsystem, Emergency decision-making subsystem, and Information management subsystem. This entire system is loaded on an AR helmet. The needed information for the system is collected with the help of AR glasses, GPS positioning, and various sensors. This information is then sent to the cloud computing platform via a 5g network communication. Then, the images are compared with the ones in the database and calculated. AR information allows efficient functioning of the various subsystems like real-time monitoring and early warning signals. Early warnings are issued and reported to the scheduling management center in case of exceptions. In case of accidents, the system is capable of identifying the actual scenes of the operation. Accidents can be classified, analyzed, and reported to the scheduling management center as soon as the alert is issued. The system is also capable of emergency decision analysis in accidents and suggests escape routes under extreme conditions, and the accident situation cannot be controlled. The author suggests that the system can prevent accidents and mitigate any damage in case of an accident [73].

4.1.11. Implementation of carbon fiber-reinforced for thermoplastic
The algorithm used in this paper is carbon-fiber-reinforced thermoplastic because of throughputs, Simultaneity by Artificial Neural networks, and random forest. Artificial Neural Network functionality is handy in this process used to classify melt-pool images according to laser power. REL is the activation function used in this model Ad Delta is the gradient-based optimizer used in this model [79]. 2 Phases: Training, Testing trained the networks by

1. Changing the number of hidden layers and keeping the number of nodes fixed at each layer
2. Changing the number of hidden layers and the nodes decreases as the layer number increases.

Figure 17 consists of the exact pathway used in the method for calculating the values. Initially, we initialize the input, and then we will define and format the network data, then define data sets training testing and validation of data creating new leads propagation of three network layers. After this, we have to train the network to equal zero if the total error is less than the final target network simulation. Otherwise, again we make the total network error equal to zero [35, 36, 38, 40, 41, 61, 67].

An effective welding technique can provide a lot more applications. There are many welding types, and mainly ultrasonic welding is the most widely used technology for joining suitable carbon fiber reinforced thermoplastic. Weld quality and load failure of tensile shear stress is predicted to be an artificial neural network [79]. These processes include a high excess of mass production. Nowadays, the weld quality and failure load can be assured by the weld quality level. The Welding process is a method that consists of vibration and monitoring some physical quantities. The significant population of manufacturing Parts performs durability and thermal tests due to high specific strength, high recyclability, and low ductility. Mainly these are getting good responses from the automotive and electronic industries. It is also believed that it is highly lightweight, and mainly, the new upcoming generations will get more attracted to this [79].

4.1.12. Application of machine learning in the control of metal melting
The Feedforward backpropagation network consists of several layers in which the first layer has a connection with network Input, and the last layer helps us give network output. The layers between the first and last layers are hidden layers, and in these layers, we can find a neuron layer [67]. Support vector regression one is nothing but Carbon support vector, regression two is nothing, but Silicon support vector tree is nothing but manganese Support vector regression four is called chromium. When comparing both the results of neural network and vector regression, the neural network has performed better analysis when compared to vector regression. We conclude that the neural network model is used in the testing and training phases, which qualifies the white cast iron production control [67].
Figure 18 consists of the exact pathway the method used for calculating the values. Firstly we will collect the historical data, then the SVM data formatting, and define the training process followed by the SVM training process. Then V cross-validation through the SVM forecasting process V cross-validation.

4.1.13. Comparison between the MLP and ANFIS to predict the surface roughness of 316L stainless steel using SLM (selective laser melting)

The MLP model has shown a better capability of predicting the non-linear relationships of the LSM. Protestantism is a modeling technique which it combines the advantages of both fuzzy logic and neural network, which in turn makes this tool one of the most accurate and suitable approaches to supervised modeling of complex processes. The fuzzy C-means clustering (FCM) technique was selected for generating the fuzzy inference reasoning system. The learning process of the ANFIS is carried out by a hybrid algorithm that combines least squares and back-propagation. ANFIS also has shown adequate results. Combining the GAs with artificial neural networks (ANN/MLP) and ANFIS enhances the modeling technique’s accuracy and efficiency. GA requires several parameters selections before starting the execution. The functional parameters of the GA were taken based on the know-how currently available for the optimization of the manufacturing process. Here, GA (genetic algorithm) is applied to reduce both models’ root mean square (RMS) [84].

The mean absolute error (MAE), correlation coefficient ($R^2$), root mean square error (RMSE) are the statistic metrics that are used in quantifying the predictions errors and also aid in validating the fitted models. The fitted MLP model has an $R$-squared statistic value equal to 0.984 and 0.953 for training (learning) and validating the model, respectively. These values are slightly higher than those that are attained from the ANFIS model. The RMSE and MAE values are lower for the MLP model when compared with ANFIS Model-based model have shown better accuracy in describing the relationship between the laser power, scanning speed and hatch spacing, and upper surface roughness. The optimized MLP scheme has attained a high precision determination coefficient (R-squared) and a homogeneous and regular distribution of the residuals. However, the prediction capability of the ANFIS-based model should not be considered weak because the statistic metrics computed also show good performance values. For optimizing the ANFIS parameters, some authors applied heuristic methods like Imperialist Competitive Algorithm, Simulated Annealing, Particle Swarm Optimization.

So these both models are almost equally suitable in predicting the surface roughness of 316L stainless steel using selective laser melting (SLM).
4.1.14. Application to melting temperatures of single and binary component solids

In summary, we have introduced regression strategies to forecast the dissolving gum-based painture of single and two-fold mixtures. Four sorts of relapse procedures work forecast models. It is tracked down that the SVR forecast model has the most influential prescient force among the four relapses[78]. Additionally, the forecast models are significantly better by considering the actual properties registered by the DFT estimation as indicator factors. The best expectation model has been developed by the SVR utilizing the indicator variable set made out of essential data and legitimate physical ties registered by the DFT estimation[80].

A blend of orderly thickness valid hypothesis (DFT) estimations and AI strategies have a broad scope of potential applications. This examination presents the blend of efficient DFT computations and relapse strategies to forecast the dissolving temperature for single and paired mixtures [80]. Here we receive the standard least-squares relapse (OLS), halfway least-squares relapse (PLSR), support vector relapse (SVR), and Gaussian interaction relapse. Among the four sorts of relapse procedures, the SVR gives the best forecast. The incorporation of actual properties figured by the DFT estimation to a set of indicator factors improves the forecast [80].

4.1.15. Comparative performance evaluation of blast furnace flame temperature prediction using artificial intelligence and statistical methods

The impact heater (BF) is the core of the incorporated iron and steel industry and used to create dissolved iron as crude material for steel. The BF has exceptionally convoluted cycle to be displayed as it relies upon multivariable interaction sources of info and aggravations. Limit functional expenses and diminish material and fuel utilization to upgrade generally speaking heater proficiency and steadiness, and furthermore to work on the lifetime of the heater inside this task [85]. Thusly, in the event that the genuine fire temperature esteem is anticipated and controlled appropriately, the administrators can keep up with fuel dispersion like oxygen improvement, impact dampness, cold impact temperature, cold impact stream, coke to mineral proportion, and pummelled coal infusion boundaries ahead of time considering the warm state changes appropriately. In this paper, fake neural organization (ANN), numerous direct relapse (MLR), and autoregressive incorporated moving normal (ARIMA) models are utilized to figure and track heater fire temperature choosing the most fitting data sources that influence this cycle boundary. All information were gathered from Eldemire Blast Furnace during 90 days of activity and the computational outcomes are palatable as far as the chosen execution.
models’ relapse coefficient and root mean squared mistake. At the point when the proposed model yields are considered for the examination, it is seen that the ANN models show preferable execution over the MLR and ARIMA models [85].

Figure 19 consist of the exact path way the method which is used for calculating beural network. Firstly, we will get the N number of inputs as weights then this all pass through a Transfer Function and then through activation function and gives the threshold and activation values.

According to MLR and model outputs, the regression between dependent variable flame temperature and remaining independent variables is 0.892 and 0.907, respectively, which shows that there is a strong correlation with selected parameters affecting the flame temperature values. When the ANN approach using the Levenberg–Marquardt and gradient descent training algorithms are considered, the regression coefficients are 0.964 and 0.945, respectively, as per model outputs. Consequently, the neural network models show better performance than the MLR and ARIMA models in terms of correlation criteria. MLR model outputs show that the minimum flame temperature is 2156.103 °C, maximum flame temperature is 2343.809 °C, and mean is 2240.364 °C, while ARIMA model outputs show a minimum flame temperature of 2164.284 °C, maximum flame temperature of 2347.968 °C, and mean of 2243.271 °C comparison of different models. (table 11)

5. Challenges and failure

Changing the number of hidden layers and keeping the number of nodes fixed at each layer in ANN. Changing the number of hidden layers and the nodes decreases as the layer number increases in the Artificial network. Predicting the susceptibility to corrosion during the process has been a big challenge.

Mainly these are getting good responses from the automotive and electronic industries. It is also believed, which has been achieved after many failures, that it is highly lightweight and mainly the new upcoming
Generations will get more attracted to this. We have to install the servers to investigate the weld quality and weld technology. These signals and servers are used as artificial intelligence (AI inputs).

Generally, the biggest challenges are:

- Big data analysis
- A detection and coordination
- KPI simulation system

Here are the three major applications of extensive data analysis are listed below:

Big data storage: here, we include raw sensor data such as temperature, pressure, process parameters generated from vibrations, and machines quality prediction bodybuilder: data pre-processing and exploring is done. Model repository: building a model.

The key issues are addressed as follows:

1. Generating the training or learning samples for ANN
2. Selecting the ANN type
3. Selecting the inputs and outputs for the model
4. Designing appropriate network architecture
5. Selecting appropriate training or learning algorithms for training the models
6. Selecting the number of hidden layers, neurons, activation functions, and other parameters of the network
7. Selecting appropriate optimization algorithms for different inputs and outputs are also called hybrid models

6. Conclusions and future directions

AM can manufacture complex-shaped parts and increase material machinability, extending technical applications unlike traditional reduction, forging, and casting processes. AM’s layered stacking features result in significant differences in product design, manufacture, and forming quality control compared to traditional manufacturing methods [43]. While fast prototyping with various materials is common, AM techniques that can handle multiple materials are limited and process-dependent.

Because AM processing parameters have such a huge impact on the printed microstructure and subsequent product performance, fine-tuning them can be difficult. Using traditional numerical and analytical models to build a process–structure–property–performance (PSPP) link for AM [44].

1. Integration of additive manufacturing (AM) with casting technology to produce massive metal parts with complicated structures [41]
2. AM emissions, ultrafine chemicals emitted during the extrusion of polymer filaments, and CO2 emission reduction through energy efficiency in industrial operations have all been studied. The study of the environmental impact of emissions from machine operations in AM systems is still a work in progress. Prototypes are increasingly being created using 3D printing techniques such as FDM. As a result, including the proposed unique and cost-effective evolutionary strategy in various 3D printing processes could reduce the amount of laser power used to determine the requisite surface attributes [30].
3. Various types of NNs [Neural Networks] in various application scenarios, including a standard MLP for linking the AM process, characteristics, and performance; a convolutional NN for AM melt pool recognition; the LSTM for recreating finite-element simulation findings; and the VAE for data augmentation [44].
4. Decentralization may be possible by the appropriate use of cloud services to distribute workload among factories/machines [8].
5. AM may play a big part in minimizing waste and energy consumption by adopting just-in-time production, a sustainability concern [8].
6. It is necessary to develop the numerical description to apply the third coordinate, energy equations, and to study the entire process of metal melting in crucibles, among other things [86].

7. Future research should be focused on using a developed numerical instrument to select the parameters of the magnetic driving system to control the liquid–solid front purposefully and to get homogeneous melt composition for metallic alloys prepared for further solidification [61].

Nowadays, the interest in ANN is increasing so that its algorithms and models have become standard tools in metal melting processes. Finally, we can say that the ANN(Artificial Neural Network) model with optimization algorithms is the best-suited and most efficient model for the metal melting processes because when it was tested for different materials with this model, we found high accuracy values rate for this model. Not only that, the structure of ANN(input layer-hidden layer-output layer) and the neurons present in each hidden layer helps in detecting the relationships between the process parameters, and also corresponding weights are assigned to each input process parameter which indicates the importance of that parameter and by these relationships, we can control the process parameters and thus the quality improves. So, ANN can be trained to execute a particular task by adjusting these weights values between the neurons, by either using the information outside the network or by themselves by responding to the input. The major advantage of ANNs is that they can be used to describe complex, multi-dimensional functional, non-linear relationships without prior knowledge about the nature of relationships. And the optimization algorithms like GA, etc, convert the values of these parameters to optimized values and help reduce the wastage of the casting process, time, etc [67, 75, 78, 87–89]. This model also uses various algorithms like the backpropagation algorithm, which helps increase the accuracy of the prediction of the outputs. With the help of ANNs, we can address the limitations of the simulation software by decreasing computational cost, time, and repetitive analysis, and this helps in replacing the need for experts for the interpretation of results and aids in implementing the online process control. If we combine any AI technology with the ANN model, the results will be more accurate. If we combine the ANN model with the RF model in calculating the ultrasonic composite welding, we can calculate the correlation coefficient more accurately in less time, with no need to do both methods independently and compare them and find the best results. The simulation model of ANN is used as an effective model for predicting the FSW process. ANN model is the best model, but combining any other model of artificial intelligence technology will make it much better, making it easy to get accurate results. Finally, we can say that the ANN model with optimization algorithms is a powerful tool in metal melting processes [80–93].

As a future interpretation, AI will also be used to predict 3D printing processes, improve the model performance of Metal additive manufacturing processes when less data is provided, and reduce the computational costs of these processes. It is also thought that the ‘ML and ANFIS technique’ usage will increase rapidly. In addition to this, it can be said that the ‘deep learning method,’ which is not used much in FSW applications, will also be implemented with increasing acceleration in future applications. Even though this paper presents how to choose the hidden layer neurons for the ANN model, it still fails in other applications while implementing those methods. So, optimum selection for hidden layer (s)/hidden neurons is still under intensive study. AI algorithms will also predict which materials to combine to make new interesting materials. Many research works are being made on producing materials such as metal-glass hybrids etc. AI techniques will also be used in melting the metal out of the rocks with sunlight. In the future, AI methods such as the data-driven computing approach will be extended to time-dependent problems like annealing processes. Machine learning will combine the governing equations with plasticity models and experimental data. AI methods should also be implemented in novel superhard materials for high-performance [87, 88, 94, 95–107].

Data availability statement

The data that support the findings of this study are available upon reasonable request from the authors.

Conflict of interest

The authors declare no conflict of interest.

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