Dedicated to Diecasting Industry

ALUCAST®

PARTNER IN PROGRESS FOR ALUMINIUM AND DIE CASTING INDUSTRY

Official Journal of Aluminium Casters' Association

Issue 154 - June 2025

USE OF AI AND MACHINE LEARNING IN ALUMINIUM DIE CASTING

Inside

www.alucast.co.in

IMPRINT

EDITOR

N. Ganeshan | natganesan72@gmail.com

EDITORIAL COMMITTEE

B. B. Lohiya | bblohiya@compaxindia.com

Rajesh Aggarwal | aggarwalrajesh1972@gmail.com

TVL Narasimha Rao | tvl.narasimharao@sundaramclayton.com

Vidhi Daryanani | vidhi.daryanani@alucast.co.in

Veena Upadhye | alucastindia@alucast.co.in

PUBLISHER

Aluminium Casters' Association (ALUCAST)

ALUCAST Membership Status (as on 29.05.2025)

Zonal Centre	Corporate	SSI	Individual	Total Members
Bangalore	8	27	8	43
Chennai	6	20	5	31
Coimbatore	1	6	2	9
Delhi	19	40	10	69
Others	6	21	2	29
Overseas	5			5
Pune	19	63	25	107
TOTAL	**64**	**177**	**52**	**293**

INDEX

ALUCAST®

PARTNER IN PROGRESS
FOR ALUMINIUM AND
DIE CASTING INDUSTRY

www.alucast.co.in

N. Ganeshan
Editor

Dear Readers,

Intelligence is commonly defined as the ability to learn, understand, and apply knowledge to solve problems, adapt to new situations, and think abstractly. Artificial Intelligence (AI) refers to machines or software that exhibit cognitive functions such as learning and problem-solving, aiming to mimic or surpass human intelligence. Artificial Intelligence fundamentally is a system / software that can perform tasks typically requiring human intelligence. These tasks include reasoning, learning, problem-solving, perception, language understanding, and even decision-making. This essentially means that computer systems have to be taught to collect enormous amount of data from different sources, taught to analyse and store them in order to access when required to perform a task. Based on the historical data and available current information, they suggest the best possible way to carry out the task.

AI (Artificial Intelligence) models in die casting, particularly those utilizing machine learning (ML), can analyse real-time data such as filling pressure curves to predict casting defects like porosity or surface imperfections. For instance, in semi-solid die casting, a Multi-Layer Perceptron (MLP) model has been developed to predict product quality by analysing injection pressure data, enabling early detection of defects and thus reducing waste. AI assists in fine tuning casting parameters, such as pouring temperature, mould temperature, and cooling rates to achieve optimal results. By analysing historical and real-time data, AI algorithms can recommend adjustments that enhance casting quality and consistency. This leads to improved yield and reduced defect rates.

AI-driven simulation tools allow for virtual testing of casting processes, enabling engineers to predict outcomes and identify potential issues before actual production. These simulations can model mould filling and solidification, helping to optimize designs and reduce the need for physical prototypes. Further, by monitoring equipment data, AI can predict when maintenance is needed, preventing unexpected downtime. This proactive approach ensures continuous operation and extends the lifespan of machinery.

Additionally, AI technology can be well employed to automate routine tasks which in turn boosts efficiency, and enables innovation in virtually every industry. AI tools optimize energy consumption by analysing and adjusting process parameters to reduce waste and improve efficiency. This not only lowers operational costs but also minimizes the environmental impact of casting processes. Moreover, AI algorithms can assist in developing new aluminium alloys by predicting the properties of various compositions. This accelerates the development process and leads to materials with better performance characteristics. AI tools can also be employed while recycling aluminium scrap materials to achieve the best composition of aluminium alloys with available scraps. This reduces the cost of raw material and also helps in reducing overall carbon footprint.

However, we would like to add a note of caution here. Depending on the source of historical data, AI Algorithms, at times, may offer biased solution. Human intervention in the form of careful consideration, is still required to make final decisions.

The integration of AI into foundry operations contributes to the development of "smart foundries," where processes are interconnected and optimized through data-driven decision-making. This aligns with Industry 4.0 initiatives, promoting automation and real-time monitoring. In summary, the application of AI in aluminium casting enhances product quality, operational efficiency, and sustainability. By leveraging AI technologies, foundries can achieve greater precision, reduce defects, and stay competitive in the evolving manufacturing landscape.

***

Use of AI and Machine Learning in Casting Simulation Software for Enhancing Aluminium Die Casting Component quality

Santhosh A.S, Pavan Ajay Raj, Dr. S Shamasundar
Aganita Ventures Private Limited

ABSTRACT

The integration of Artificial Intelligence (AI) and Machine Learning (ML) into casting simulation software is revolutionizing the way foundries design and optimize die casting processes. Unlike traditional casting simulation methods that rely solely on physical modeling and user expertise, AI and ML enable the software to learn from historical data, recognize patterns, and make intelligent predictions.

This data-driven approach significantly enhances defect detection accuracy, particularly for issues like shrinkage porosity, air entrapment, cold shuts, misruns, blowholes. As a result, casting simulation tools empowered by AI and ML are becoming essential for die casting manufacturers striving to improve efficiency, minimize defects, and remain competitive in a technologically advancing manufacturing landscape.

The Advanced Defect Prediction Tool (ADPT), developed in ADSTEFAN casting simulation software by Hitachi ICS Japan, represents a significant step forward in intelligent casting analysis. By integrating machine learning techniques, ADPT enables users to identify potential casting defects more rapidly and with greater precision than conventional methods. This paper presents a detailed case study and real-world applications that demonstrate the effective integration of ML algorithms with simulation platforms has led to notable gains in operational efficiency, as well as marked improvements in component quality.

Keywords: Artificial Intelligence, Machine Learning, Die Casting, Casting Simulation, Advance Defect Predication Tool (ADPT), ADSTEFAN, Hitachi ICS

INTRODUCTION

Casting is one of the oldest and most widely used manufacturing processes, playing a crucial role in producing complex metal components for a variety of industries, including Aerospace, Automotive, Railways, Marine, Defense, General Engineering. Aluminium die casting has emerged as a preferred method for mass-producing lightweight, high-strength parts with excellent dimensional accuracy and surface finish. While this method offers high productivity and repeatability, it also presents challenges such as porosity, incomplete filling, cold shuts, and thermal stresses, which can compromise product integrity.

To address these issues, casting simulation software has become an essential tool in the design and validation of die casting processes. These tools enable engineers to predict fluid flow, solidification behavior, and potential defect zones before actual production begins. However, traditional simulation approaches often require expert interpretation, extensive computational resources, and multiple iterations. The advent of Artificial Intelligence (AI) and Machine Learning (ML) is revolutionizing this landscape. By enabling data-driven analysis, and intelligent prediction, AI/ML technologies are enhancing the accuracy and efficiency of casting simulations.

ARTIFICIAL INTELLIGENCE:

Artificial Intelligence (AI) refers to the simulation of human intelligence in machines that are programmed to think, learn, and make decisions. AI technologies include machine learning (ML), computer vision, natural language processing (NLP), neural networks, and expert systems. These systems can process large datasets, identify patterns, optimize processes, and even predict future outcomes.

MACHINE LEARNING:

Machine learning is a subfield of artificial intelligence (AI) that focuses on the development of algorithms and statistical models that enable computer systems to learn and make predictions or decisions without being explicitly programmed.

Machine learning has two objectives:

- To classify data based on models which have already been developed
- To make future predictions based on developed models / datasets.

ROLE OF AI/ML IN CASTING INDUSTRIES:

Real-Time Process Control: AI enables adaptive control systems that adjust process parameters in real time based on live sensor feedback. This maintains process stability, ensures uniform quality, and reduces reliance on operator experience.

Simulation & Design Improvement: AI enhances traditional casting simulation tools by learning from past simulations and real-world production outcomes.

Defect Prediction and Prevention: AI models analyze historical and real-time process data to predict common casting defects such as porosity, shrinkage, and cold shuts. Smart Production Planning & Inventory Management: ML-based forecasting models predict demand trends, streamline production schedules, and optimize inventory levels.

Automated Quality Inspection: AI-driven computer vision systems detect surface and internal defects using camera or X-ray images with high accuracy.

Energy and Resource Efficiency: AI identifies energy inefficiencies and material waste across operations. By optimizing resource usage, it supports sustainability goals while reducing operational costs.

In this paper we are going to analyze the role of AI/ ML in Defect Prediction and Prevention and Simulation and Design Improvement.

IMPLEMENTATION OF MACHINE LEARNING IN CASTING SIMULATION SOFTWARE:

Machine learning (ML) plays a crucial role in casting simulation software, enhancing its capabilities and improving the accuracy of predictions and simulations. The integration of ML techniques with casting simulation software adds a layer of intelligence and predictive capabilities, allowing engineers and manufacturers to optimize casting processes and improve the quality of cast components.

Some of Benefits of implementing Machine learning in Casting simulation software:

Improved Accuracy: Machine learning algorithms can analyze vast amounts of historical casting data, including process variables, material properties, and outcomes.

Enhanced Predictive Modeling: ML can improve predictive models used in casting simulations. For example, it can better predict solidification patterns, shrinkage, and defects by learning from past simulations and real-world data.

Defect Detection and Prevention: ML algorithms can help detect potential defects in the casting process by analyzing data in real-time. This allows for immediate corrective actions and reduces the likelihood of producing defective castings.

Faster Simulation Times: ML can accelerate simulation times by optimizing the simulation parameters and focusing computational resources on critical areas of the casting process, reducing the time and resources required for simulations.

Optimized Process Parameters: Machine learning can identify optimal process parameters, such as pouring temperature, mold design, and gating systems, by analyzing historical data and their impact on casting quality.

Decision Support: Machine learning can provide decision support tools for engineers and operators by offering insights and recommendations based on historical data and ongoing simulations.

Continuous Learning and Improvement: Machine learning allows casting simulation software to continuously learn and adapt to new data, trends, and production conditions, ensuring that simulations remain relevant and accurate over time.

By analyzing above benefits simulation software's existing in present market are exploring this technology for better

ADVERTISEMENT TARIFF FOR NON-MEMBERS								
Revised w.e.f 01 April 2024								
Advertisement Placement	Six Issues				Single Issue			
	Basic (₹)	Total with GST (₹)	Basic (US$)	Total with GST (US$)	Basic (₹)	Total with GST(₹)	Basic (US$)	Total with GST(US$)
Back Cover Page	121000	142780	2662	3141	-	-	-	-
Front Inner Page	96800	114224	2178	2570	-	-	-	-
Back Inner Page	84700	99946	1875.5	2213	-	-	-	-
Inside pages	42350	49973	931.7	1099	8770	10348.6	211.75	250

ADVERTISEMENT TARIFF FOR MEMBERS								
Revised w.e.f 01 April 2024								
Advertisement Placement	Six Issues				Single Issue			
	Basic (₹)	Total with GST (₹)	Basic (US$)	Total with GST (US$)	Basic (₹)	Total with GST(₹)	Basic (US$)	Total with GST(US$)
Back Cover Page	114950	135641	2528.90	2984	-	-	-	-
Front Inner Page	91960	108513	2069.10	2442	-	-	-	-
Back Inner Page	80465	94949	1784.75	2106	-	-	-	-
Inside pages	40232.5	47474	883.30	1042	8391.35	9902	201.1625	237

GST @ 18%

ADVERTISEMENT SIZES & FILE FORMAT	
Full Page	**Final Trim Size:** Width 210mm X Height 297mm **Bleed:** 3mm all sides
Half Page	Width 180mm X Height 135mm (non-bleed)
Quarter Page	Width 90mm X Height 135mm (non-bleed)
File Format	Print ready PDF in CMYK color space. No spot colors. All fonts embedded & images @ 300dpi resolution

Please send cheque in the name of ALUMINIUM CASTERS' ASSOCIATION (ALUCAST) payable at Pune to:

ALUCAST®
PARTNER IN PROGRESS
FOR ALUMINIUM AND
DIE CASTING INDUSTRY

Aluminium Casters' Association (ALUCAST)
702, AMar Neptune, Baner Road, S. No. 6/1/1
Plot No. 45, 46A, 46B, Pune 411045
T: +91 20 27290014 E: alucastindia@alucast.co.in

defect prediction and Advance Defect Predication Tool (ADPT) in ADSTEFAN Casting simulation software is one such tool developed by Hitachi ICS Japan which will help users to analyze defects in less time and higher prediction accuracy using Machine Learning. This tool uses master data or database created by users to predict defects in target project by Machine Learning. Fig 1.1 shows analysis process flow:

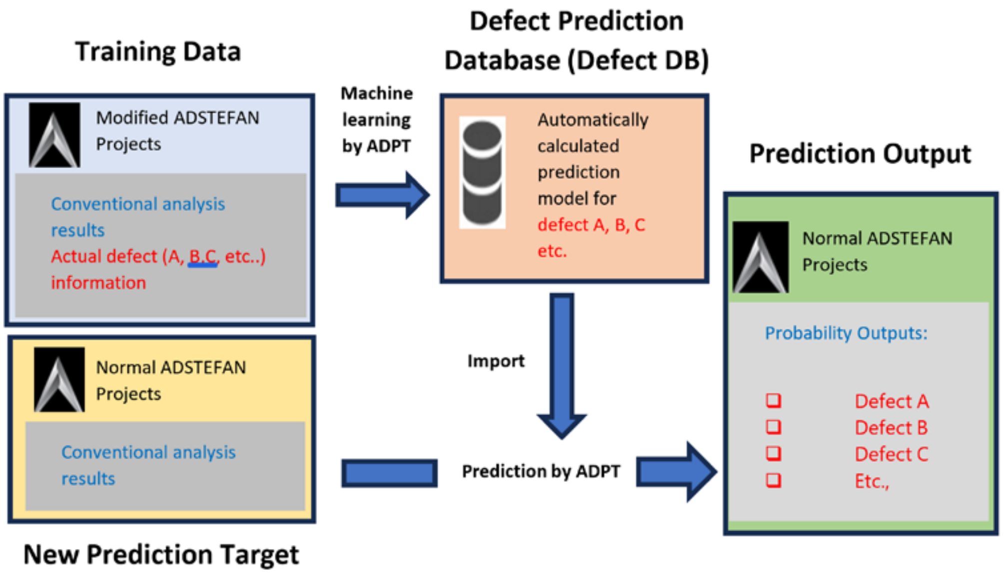


Fig 1.1 – Analysis Process Flow Chart

Defect prediction can be used for target projects of same cast alloy with different casting design and process parameters. Defect database for defects like flow marks, cold shuts, misrun, gas porosity, inclusions, shrinkage, warpage, etc., can be created.

Steps in ADPT:

Below are steps for Advance Defect Prediction Tool (ADPT)

- Register the corresponding actual defect information and use it as Master data.
- Create a defect prediction database by machine learning one or more Master data.
- By inputting the analysis result of a new normal project into this database, we will provide a system for making the next prediction.
- Since the output by ADPT is based on the actual defect information registered in the Master data, the output result is not an indirect index but a more direct and specific defect occurrence rate.

Benefits of ADPT:

- More accurate defect prediction can be done compared to conventional method as
- Defect prediction is done by using past shop floor results data.
- Past learning data is stored in database that can be utilized for future projects.
- Wider range of defects can be predicted compared to conventional method.
- More range of defects can be predicted within less time.

CASE STUDY FOR DEFECT PREDICTION USING MACHINE LEARNING:

We will demonstrate a case study to understand defect prediction by Machine Learning. To implement ADPT, products should be of the same material grade and casting process.

Machine Learning uses data of defect type and defect intensity for prediction in target project.

Training data preparation:

For training data preparation, we have identified the casting part as shown in below fig 1.2. The process is High Pressure Die Casting and material is ADC 12. We are going to train simulation software on Shrinkage porosity defect prediction.

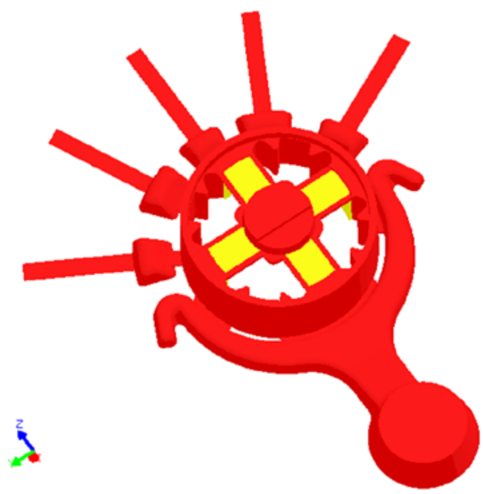
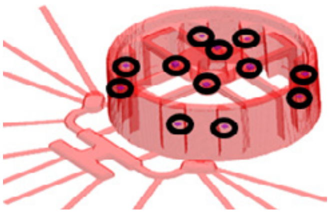


Fig 1.2 – Model considered for Training data

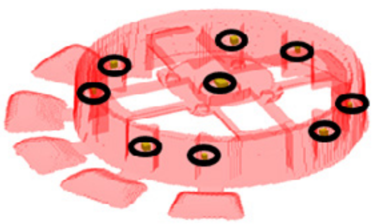
For training data, we have considered 3 iterations with change in gating design and same pouring is done on shop floor and shrinkage porosity locations are identified as per below fig 1.3 for iteration 1. Defect intensity is observed 0.8 as per locations displayed in fig 1.3.



Defect Intensity – 0.8

Fig 1.3– Iteration 1 Shrinkage porosity defect

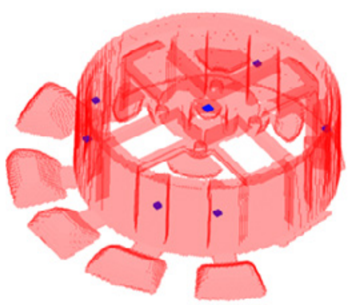
For the second iteration, the Methoding system is redesigned to overcome shrinkage porosity defect as per fig 1.4. As per shopfloor casting observation, intensity of defect is reduced from 0.8 to 0.4.



Defect Intensity – 0.4

Fig 1.4 – Iteration 2 Shrinkage porosity defect

For the third iteration, the Methoding system is redesigned to overcome shrinkage porosity defect as shown in 1.5. As per shop floor casting observation, we have reduced intensity defect from 0.4 to 0.2.



Defect Intensity – 0.2

Fig 1.5 – Iteration 3 Shrinkage porosity defect

Above 3 iteration details are collected from the shop floor and master defect database is created in ADSTEFAN simulation software and this data can be referred to any project with High Pressure die casting process with material ADC 12.

Implementation of Trained data for new project:

Now with created set database for defects – shrinkage porosity defect in ADPT, we will implement in Project B to determine probability and locations of defect. We have identified Project B as per fig 1.6. Process is HPDC and the Material is ADC 12.

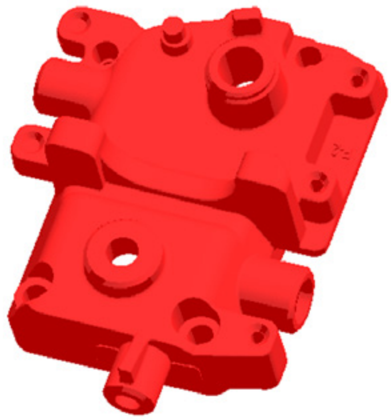


Fig 1.6 – Model considered for implementation of trained data

We have observed that probability of Shrinkage porosity defect in Project B. Below figure 1.7 are results for Defect prediction using Machine learning tool – ADPT for defects – Shrinkage Porosity defect.

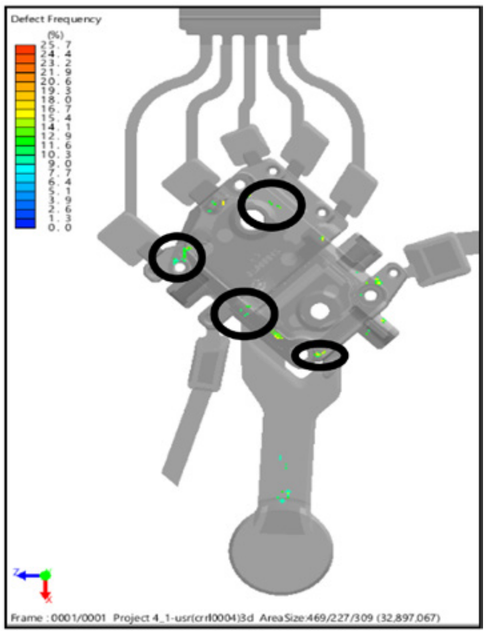


Fig 1.7 – Shrinkage porosity defect prediction using ADPT Tool

Correlation between Shopfloor and ML Predicted defects:

Actual shop floor pouring is done based on model considered in Project B and we have observed Shrinkage porosity defect in locations identified as per ADPT results. Fig 1.8 shows comparison between shop floor defect results and ADPT results.

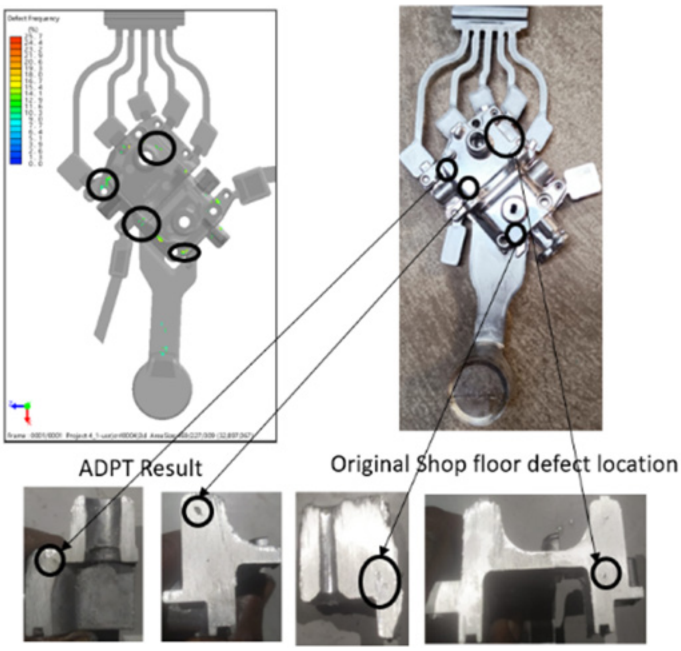


Fig 1.8 – Correlation between Shopfloor and ADPT

CONCLUSION:

The integration of Artificial Intelligence (AI) and Machine Learning (ML) into casting simulation software marks a significant advancement in the aluminum die casting industry.

Casting simulation software are adapting these new technologies such as machine learning in their tool in order to achieve more accurate prediction rate of defects and thus helping foundrymen to take necessary actions to produce good sound castings in lesser lead time.

In this paper, we have explored the roles AI and ML play in improving casting quality by accurate defect prediction. The shop floor results are validated with data-driven simulations and found improvement in defect prediction within lesser time compared to conventional casting simulation analysis. As foundries continue to adopt Industry 4.0 practices, AI and ML will play an increasingly central role in casting process optimization, ensuring higher quality, lower costs, and improved sustainability. The findings of this study underscore the potential of AI/ML to transform traditional manufacturing into a more intelligent and efficient operation, setting new standards for quality and innovation in aluminum die casting.

REFERENCES:

- Industry 5.0: Top 3 Things You Need to Know - By James Jardine, Staff Writer, MasterControl.
- Machine learning by Ed Burns.
- https://info.hitachi-ics.co.jp/eng/products/adstefan/about/index.html
- Industrial (R)evolution by Swati Verma
- Industry 5.0: An Industry that based on the Use of Collaborative Robots: https://www.industrialautomationindia.in/industryitm/10404/Industry-5.0:-An-Industry-that-based-on-the-Use-of-Collaborative-Robots/industry

ACKNOWLEDGMENT:

We thank Hitachi ICS and ADSTEFAN team for their continuous support.

Dr. S. Shamasundar
Managing Director
E-mail: shama@pro-sim.com

Santhosh Kumar A.S.
General Manager - Casting Operations
E-mail: santhosh.as@aganita.in

Pavan Ajay Raj
Sr. Application Engineer
E-mail: ajay.raj@aganita.in

ALUCAST® 2025

TECHNICAL CONFERENCE & TABLE TOP EXHIBITION
HOTEL DOUBLE TREE BY HILTON, PUNE | 25th & 26th NOVEMBER 2025

PREMIER 2-DAY CONFERENCE AND TABLE TOP EXHIBITION

25th & 26th NOVEMBER 2025

HOTEL DOUBLE TREE BY HILTON
TATA MOTORS ROAD, CHINCHWAD, PUNE

THEME: EFFECTIVE APPLICATION OF MODERN TECHNOLOGY IN CASTING PROCESSES

KEY HIGHLIGHTS:

- Technical Paper Presentations
- Product Presentations
- Table-Top Display
- Startup Pitch
- 15+ Expert Speakers
- 10+ Exhibitors
- 350+ Industry professionals and decision makers

SPONSORSHIP OPPORTUNITIES

- Platinum Partner - INR 4,00,000
- Gold Partner - INR 2,00,000
- Prime Partner - INR 1,50,000
- Sustainability / Knowledge Partner - INR 1,00,000
- Startup Pitch Partner - INR 50,000
- Delegate kit partner - INR 50,000
- Exhibition Area partner - INR 35,000
- Gifts partner - INR 35,000
- Handouts partner - INR 10,000

PARTICIPATION FEE	ALUCAST MEMBER	NON-MEMBER
DOMESTIC DELEGATES	INR 9,500.00	INR 11,500.00
OVERSEAS DELEGATES	US$ 180.00	US$ 250.00
PRODUCT PRESENTATION	Domestic INR 50,000.00 | Overseas US$ 800.00	
TABLE TOP DISPLAY	Domestic INR 55,000.00 | Overseas US$ 850.00	

GST @ 18% applicable extra

CALL FOR PAPERS

THEME: EFFECTIVE APPLICATION OF MODERN TECHNOLOGY IN CASTING PROCESSES

Topics Suggested for Technical Papers at ALUCAST® 2025 Technical Conference

- Qualitative check by using X-ray and CT scan analysis
- Preparing for CBAM - Carbon border adjustmentmechanism for casting exports
- Thermal Management of dies by:
  - Thermal cameras
  - Heating & cooling units
  - Jet cooling units
  - Programmable pressure and flow controlled water cooling systems
- New Aluminum Alloys that can effectively replace primary Die casting Aluminum Alloys
- Critical aspects of designing the dies
- Energy management & conservation in Aluminum melting
- Recent advances in CPDC - Counter Pressure Die Casting technology
- Effective use of automation & Robots in Die casting Industry
- Application of vacuum technology in diecasting process
- Use of Additive manufacturing techniques in Die casting process
- Improving the quality of molten metal

TIMELINES

Submission of Abstract (MS Word)	Monday, 30th June 2025
Submission of Full-Length Paper (MS Word)	Friday, 15th August 2025
Approval By Alucast	Monday, 15th September 2025
Submission of Presentation by Author (PPT)	Wednesday, 15th October 2025

YOUR CONTACTS

Ms. Vidhi Daryanani
Secretary-General
vidhi.daryanani@alucast.co.in
M: +91 70201 98752

Ms. Veena Upadhye
Senior Executive - Administration
veena.upadhye@alucast.co.in
T: +91 20 2729 0014

Ms. Vaishali Thombare
Executive - Marketing
vaishali.thombare@alucast.co.in
M: +91 89569 31329

www.alucast.co.in

ALUCAST® Signs MoU with MIT World Peace University to Strengthen Industry-Academia Collaboration

We are delighted to announce that ALUCAST® has entered into a Memorandum of Understanding (MoU) with Dr. Vishwanath Karad MIT World Peace University, Pune, on May19th, 2025.

This partnership marks a pivotal moment in aligning academic learning with industry needs in the aluminum die-casting sector. The MoU outlines a comprehensive collaboration that includes:

- **Academic Integration:** Introduction of a dedicated elective program on die casting at Diploma, Graduate, and Postgraduate levels, with ALUCAST® contributing to curriculum development and faculty training.
- **Industry Exposure:** Facilitating student internships, live industrial projects, factory visits, and hands-on training programs.
- **Faculty and Student Development:** Organizing guest lectures and faculty development initiatives to ensure contemporary industry knowledge transfer.
- **Research and Innovation:** Joint R&D projects, publications, and initiatives to promote sustainable manufacturing and process improvements.
- **Workforce Upskilling:** Offering continuing education and management development programs for professionals in the die-casting industry.

This collaboration reflects ALUCAST®'s commitment to nurturing talent, driving innovation, and building a resilient, future-ready ecosystem for aluminum die casting in India.

***

ALUCAST'S Visit to Vishwakarma Institute of Technology Corporate Office

ALUCAST recently visited the corporate office of Vishwakarma Institute of Technology (VIT). Among various topics of mutual interest, the challenge of skilled labour in the die-casting industry featured prominently in the discussions.

Both parties agreed to collaborate on a joint initiative aimed at channelizing and developing skilled labour to meet the specific needs of the die-casting sector.

Both parties will strive to bridge the industry-academia gap and foster a stronger, future-ready workforce for the aluminium die-casting ecosystem.

ALUCAST® Activities held in April - May 2025

Workshop Title	Project Management Workshop
Trainer	Mr. Ravindra Kale – a distinguished industry expert, visiting faculty at leading B-Schools in India, and former General Manager at Mahindra & Mahindra
Date	Tuesday, 22nd April 2025 & Wednesday, 23rd April 2025
Time	10:30 AM to 06:00 PM
Location	Force Motors Limited, Training Centre, Mumbai-Pune Road, Akurdi - 411035
Duration	2 Days

Content – Project Management:

Day – 1

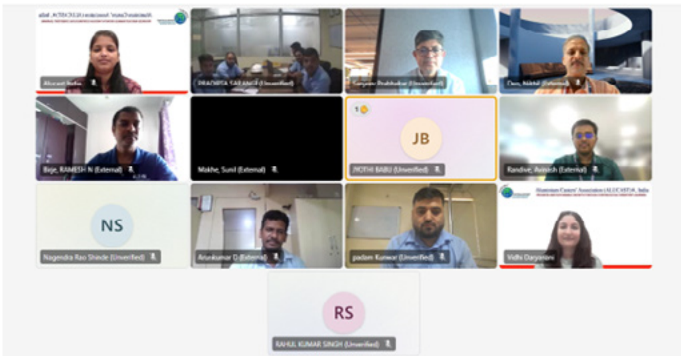
- Overview of Project Management: Concepts and attributes of Project, Project lifecycle and stake holders, Scope and priorities
- Learning of Learning of Pre-feasibility, Specific Functional Studies (e.g., Facility Location study) & Feasibility culminating into preparation of DPR
- Project Life Cycle, WBS (Work Break down Structure)
- Project Planning: Time and cost estimates with AON and AOA conventions, Budget estimates, PERT network analysis for probabilistic projects

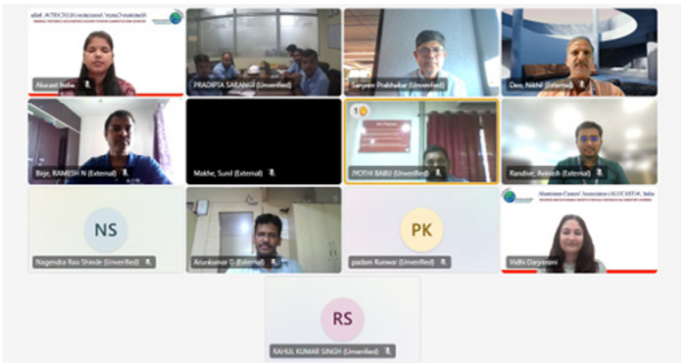
Day – 2

- Network Analysis & Crashing Concepts
- Project Scheduling & Control: GANTT Chart
- Resources Allocation / Levelling: Minimizing the use of resources and working out the optimal plans with least resources without project delay
- Earned Value Analysis: 'S' Curve, Cost and Schedule performance
- Financial Appraisal: Debt Service Coverage Ratio (DSCR) & Interest Coverage Ratio (ICR), Non-Discounting Methods (e.g. Pay Back Period, Accounting Rate of Return) & Discounting Methods (e.g. NPV, IRR, BCR)
- Project Organization: Different Structures, Role and responsibilities of Project Manager

***

Workshop Title	PQ² Diagram
Trainer	Mr. Sanjeev Prabhakar, Vice President R&D Business Excellence & PE - Rockman Industries Ltd.
Date	Wednesday, 14th May 2025
Time	10:00 AM to 12:00 Noon
Location	Microsoft Teams
Duration	2 hours





Topic Insights:

- Why PQ^2
- Brief on the Physics of PQ^2
- Parameters of Interest in PQ² Analysis
  - Machine
  - Die Line (Tooling)
  - Minimum Flow Rate
  - Process Window of PQ²

***

From Simulation to Solution: AI-Enabled Optimization in Aluminium Die Casting

- Sanjay J, Sendil Kumar K, Kaushik B & B Ravindran
Kaushiks International - Bangalore

INTRODUCTION

Aluminium die casting is widely used for producing complex, high-precision parts at scale. Ensuring consistent quality requires tight control over variables like gate design, plunger speed, cooling layout, and venting—all of which influence flow behaviour, cooling, and defect formation.

To manage this complexity, engineers rely on casting simulation tools that help evaluate designs and process settings virtually, reducing the need for costly physical trials.

However, simulations are often used in a trial-and-error fashion, requiring engineers to manually test many combinations and monitor each iteration—making the process time-consuming and heavily dependent on human intervention. As part complexity and performance demands increase, there's a growing need to move beyond passive evaluation.

This is where optimization and closed-loop decision-making come in. By defining clear objectives and using intelligent algorithms to explore design and process combinations, engineers can reduce manual effort and discover optimal solutions more efficiently. This paper explores how such optimization techniques, when combined with simulation, enhance die casting design and process development.

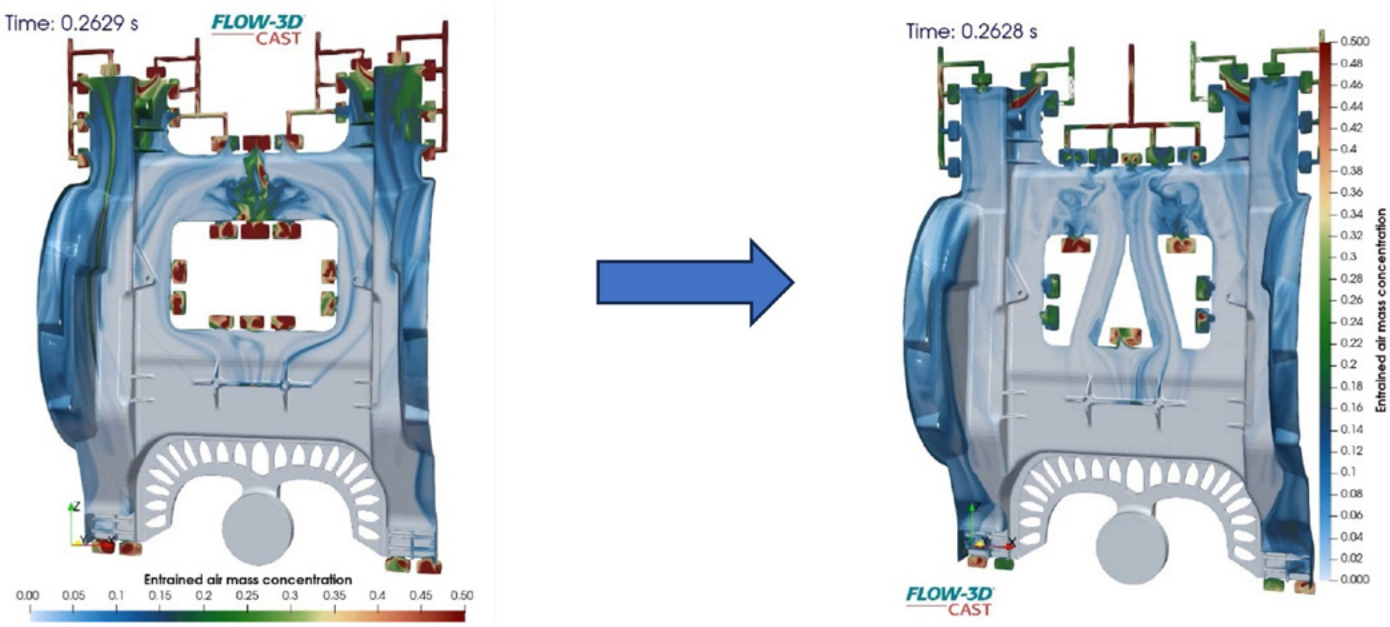


Fig 1a Initial Design

Fig 1b Optimized Design

LIMITATIONS OF CURRENT PRACTICE

Despite advances in casting simulation, most current workflows still operate in an open-loop manner. Engineers manually adjust parameters, run simulations, interpret results, and iterate based on experience. Each cycle requires human intervention and close monitoring, which makes the process time-consuming and limits the ability to explore the full range of design and process options. This often results in suboptimal solutions, especially when faced with complex geometries, tighter quality requirements, and shorter development timelines.

To address these challenges, there is a growing need to close the loop between simulation and decision-making. By integrating optimization techniques directly into the simulation process, engineers can define objectives—such as minimizing porosity or balancing gate flow—and let intelligent algorithms automatically guide the search for the best outcomes. This approach reduces manual effort, improves repeatability, and allows for broader exploration of the design space within a shorter time frame.

LIMITATIONS OF THE TRADITIONAL (OPEN-LOOP) PROCESS:

- Relies heavily on manual tuning and expert intuition.
- Each simulation cycle requires hands-on setup and review.
- Time and resource constraints often limit the number of design iterations.
- Exploration of the design space is narrow and inefficient.
- Difficult to guarantee truly optimal outcomes.

WHY A CLOSED-LOOP APPROACH IS NEEDED:

- Automates the feedback from simulation results into the next iteration.
- Reduces human workload and increases consistency.
- Enables targeted optimization based on specific quality or performance goals.
- Enhances decision-making with automated data-driven insights.
- Supports faster, more reliable development of high-performance castings.

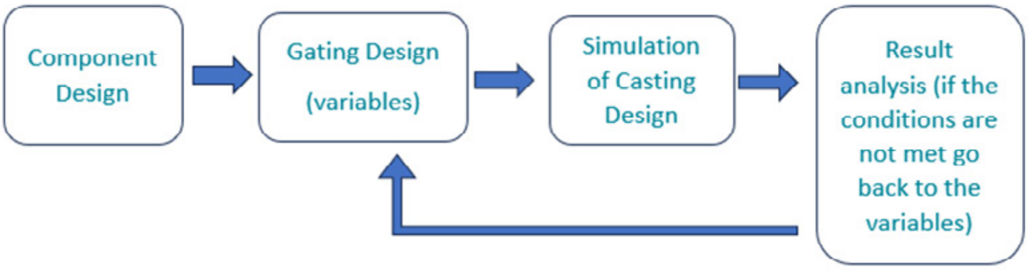


Fig 2 Closed-Loop Optimization Workflow Using AI and Simulation

ROLE OF AI AND MACHINE LEARNING IN CASTING SIMULATION OPTIMIZATION

In aluminium die casting, achieving consistent part quality while minimizing defects such as porosity, air entrapment, or cold shuts requires precise control over multiple variables—from gating dimensions to plunger velocity profiles. While CFD simulation tools have become standard practice for analysing metal flow and solidification, the process of optimizing these simulations has traditionally relied on manual tuning and expert judgment. This makes the design and process development effort time-consuming and difficult to scale across multiple components or product lines.

To address this, AI and machine learning techniques are now being integrated into optimization tools to intelligently guide casting simulation workflows. The core idea is to shift from simply running and analysing simulations to using algorithms that learn from each run and automatically suggest improved design or process changes.

At the heart of this approach is the use of surrogate models—mathematical functions that approximate the behaviour of full CFD simulations based on a limited number of evaluated designs. These models are trained using sampled points from early simulations and refined through iterative feedback. One commonly used technique is Radial Basis Function (RBF) interpolation, which creates a response surface that maps how changes in input variables (e.g., gate thickness or metal temperature) affect outcomes like porosity or fill time.

Once this response surface is built, intelligent search algorithms—such as evolutionary methods, global optimizers, and local refinement techniques—can explore the design and process space efficiently. These algorithms mimic how AI systems learn from data: each simulation iteration provides new insight that sharpens the model's predictions, helping it guide the search toward optimal results without evaluating every possibility directly.

Some advanced platforms incorporate a budget-based solver approach, allowing users to define a limit on the number of simulations. The tool then allocates these simulation runs intelligently, targeting the areas of the design and process space most likely to yield meaningful improvements. This is especially valuable in casting, where a single high-fidelity simulation can take hours.

To understand how optimization works in casting, imagine that we are trying to find the best possible combination of process and design settings—like gate size, metal temperature, or plunger speed—that gives us the best casting quality.

$$\min_{x \in D} f(x) \quad \text{such that} \quad g(x) < 0$$

This can be written mathematically as:

- X represents the set of design or process inputs (like gate width, velocity, etc.)
- D is the allowed range for these inputs.
- f(x) is the result we want to improve—like minimizing porosity or air entrapment.
- g(x) means we have limits or rules to follow, like not exceeding maximum pressure or solidification time.

If we are only trying to improve one thing—like porosity—this is called a single-objective problem. The best solution, called the optimum, is the set of inputs that gives the lowest porosity while staying within the allowed limits.

This equation tells the optimization tool to search for that best combination of parameters instead of testing hundreds of possibilities manually. It helps turn experience-driven decision-making into a smart, automated process based on clear goals.

The entire process functions as a closed-loop optimization cycle. It begins with a proposed design, followed by simulation and analysis of the results. These results are used to build or refine the surrogate model, which in turn guides the optimization engine in selecting the next most promising configuration to evaluate. This loop continues until a stopping condition is met—often defined by either a computational budget or convergence to an optimal result. At each step, the system becomes smarter and more focused, continuously learning from past simulations. This approach reduces manual intervention, accelerates decision-making, and ensures that final design and process choices are backed by data and mathematical certainty, not just engineering intuition.

Tools like FLOW-3D(x) and other simulation optimization platforms are increasingly enabling this intelligent casting workflow, bringing the power of AI and ML to the foundry floor—one simulation at a time.

TIME SAVINGS WITH AI-DRIVEN OPTIMIZATION

A significant benefit of using AI-driven optimization tools like FLOW-3D(x) is the reduction in total time spent on achieving the optimal design. Traditional workflows require manual result interpretation and geometry adjustments between simulations, whereas the optimization tool automates these tasks, saving both time and effort.

Process Step	**Traditional Workflow**	**AI-Driven Optimization**
Number of Iterations	7 iterations	7 iterations
Simulation Time per Iteration	4 hours	4 hours
Manual Analysis and Geometry Changes	2 hours per iteration × 6 transitions = 12 hours	0 hours (fully automated)
Total Time Required	**(7 × 4) + 12 = 40 hours**	**7 × 4 = 28 hours**
Total Time Saved	**—**	**12 hours saved**

CASE STUDY: RUNNER BALANCING OPTIMIZATION IN ALUMINIUM DIE CASTING- COURTESY- FORM SRL

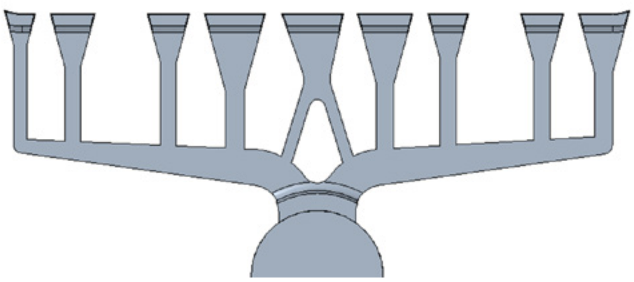
In this case study, an AI-assisted optimization approach was applied using FLOW-3D(x)) to improve runner balancing in a complex aluminium die casting component. The primary objective was to ensure that molten metal reached all gates simultaneously, minimizing flow imbalance, air entrapment, and related defects during cavity filling.

Initial Design Challenge

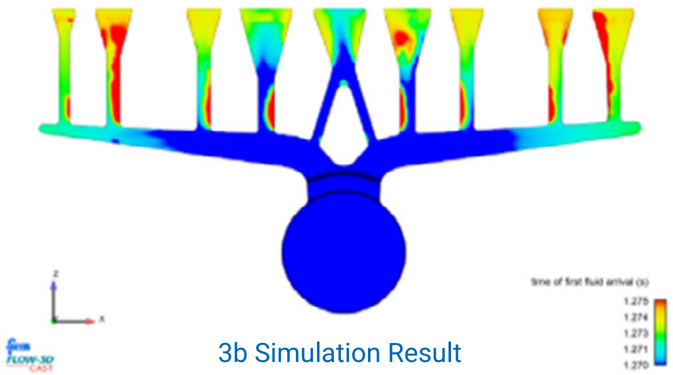
The casting system consisted of:

- 8 side runners, each connected to gates that were initially positioned perpendicular to the runner axis (i.e., at 0° or 90°)
- 2 central runners, initially oriented at 17°
- Terminal extensions located at the ends of the runners

This configuration led to variations in metal arrival time across the gates, contributing to fill imbalance and potential cold shut risks.



3a Initial design



3b Simulation Result

Optimization Variables and Design Limits

To address this, three key parameters were selected for optimization:

1. Gate orientation on side runners:
- Adjustable between 0° and 14° to align flow direction with the gate axis.

2. Central runner angle:
- Varying from 17° to 30°, allowing redirection of flow and improved balance.

3. Terminal length at runner ends:
- Ranging from 0 mm to 20 mm, used to fine-tune pressure drop and control timing.

All geometry modifications were implemented through a CAD-integrated interface, enabling seamless updates in each iteration. These parameter variations were then evaluated using FLOW-3D(x) 's built-in surrogate-based optimization engine.

Optimization Methodology

The optimization process used Design of Experiments (DOE) to generate initial sample points, followed by surrogate model generation and multi-objective optimization. The key performance indicators included:

• Arrival time deviation at gates

• Flow uniformity index

• Entrained air volume

FLOW-3D(x) dynamically refined the design space using an intelligent solver, balancing improvement with computational budget.

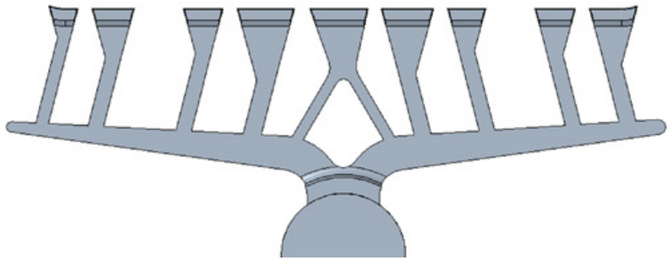


Fig 4a Finalized Design

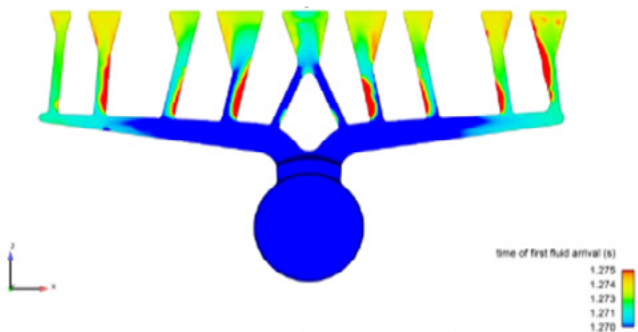


Fig 4b Results of finalized design (the result shows the time of metal arrival at the gates)

The optimized design ensured uniform metal arrival at all gates, resolving flow imbalance and reducing defect risks. At the same time, the optimization process minimized air entrainment by refining gate angles and runner geometry accordingly.

This parallel approach led to a balanced, low-defect fill, demonstrating the effectiveness of AI-driven, simulation-guided optimization in improving casting quality with fewer iterations.

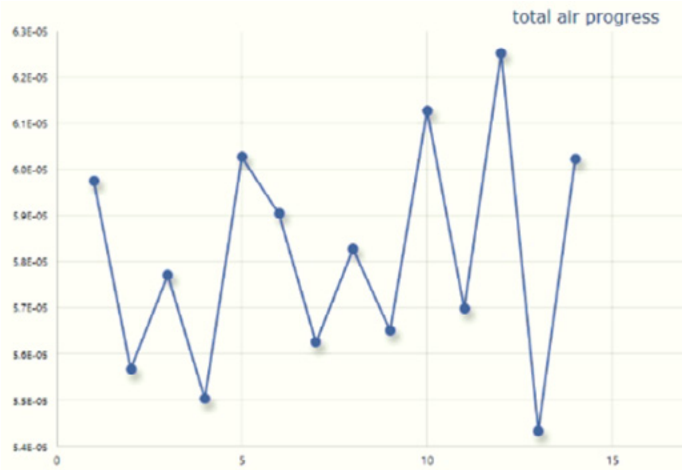


Fig 4c Air entrapment in the cavity- the lowest air progress is in the 14 iteration.

CONCLUSION

Integrating AI-driven optimization into die casting simulation offers clear advantages in both design and process improvement. Closed-loop workflows replace repetitive trial-and-error with intelligent, data-guided decision-making—enabling faster exploration of better solutions while reducing manual effort.

Modern platforms like FLOW-3D(x) are built for practical use on the shop floor, offering intuitive interfaces that allow users to set objectives and constraints without needing deep AI or mathematical expertise. The optimization engine works in the background, automating strategy selection and helping engineers focus on solving real casting challenges. As shown in the runner-balancing case study, combining simulation with closed-loop optimization leads to more balanced flow, lower defects, and fewer iterations. These tools can also be extended to optimize cooling, venting, or cycle time—improving casting quality and efficiency across the board.

The future of casting lies in accessible, simulation-guided optimization—integrated into everyday workflows and empowering foundries to innovate faster, reduce defects, and deliver consistently high-performance parts.

REFERENCES

- FLOW-3D(x)) User Manual. Flow Science, Inc.
- FLOW-3D CAST User Manual. Flow Science, Inc.
- Flow Science. (2023). Case Studies in Casting Optimization.

***

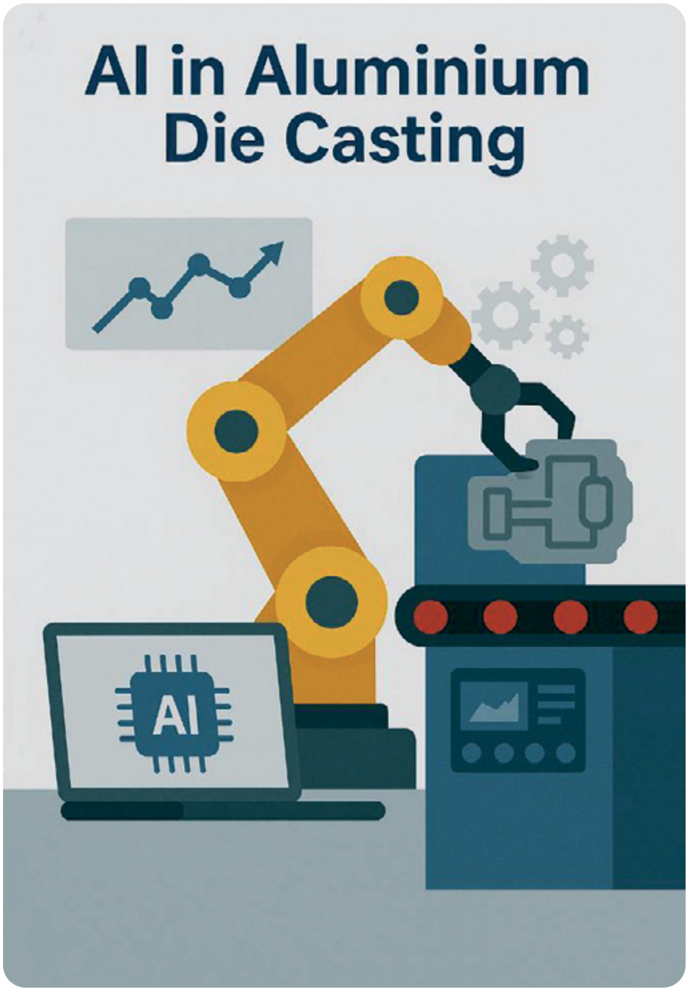
Smarter Foundries: Harnessing AI and Machine Learning in Aluminium Die Casting

- G Praburam, Alubee Die Casters

"The factories of the future will have only two employees: a man and a dog. The man is there to feed the dog. The dog is there to stop the man from touching the machines."

-Warren G. Bennis

INTRODUCTION



The aluminium die casting industry is no stranger to evolution. From manual processes to high-speed machines, from craftsmanship to simulation,every leap has defined a new level of excellence.

Today, we stand at the cusp of another defining transformation: the integration of Artificial Intelligence (AI) and Machine Learning (ML).

As casting tolerances shrink and customer expectations rise, foundries must move beyond traditional controls and lean into intelligent, adaptive systems. AI and ML are not merely digital tools,they are enablers of precision, productivity, and predictability in the complex world of aluminium die casting.

EXTRACTS

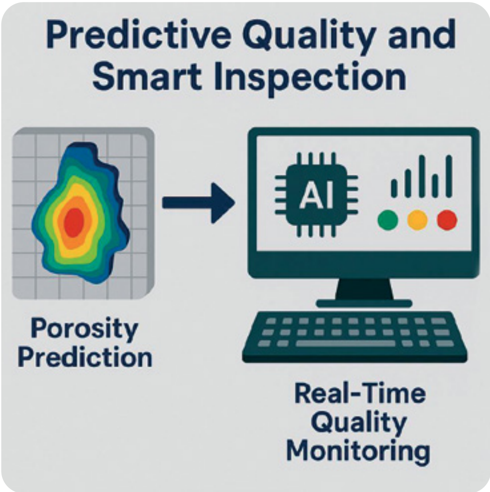
AI and Machine Learning are revolutionizing aluminium die casting by:

- Predicting and preventing casting defects
- Optimizing process parameters in real-time
- Accelerating die design and development
- Managing energy usage and sustainability targets
- Enhancing supply chain predictability and shop-floor efficiency

This article explores real-world applications, potential benefits, and future directions,tailored to help Alucast members envision smarter foundries.

1. Predictive Quality and Smart Inspection

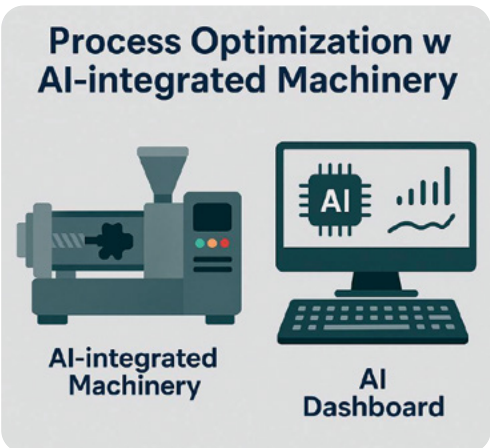
ML algorithms use historical data,like melt temperatures, plunger speeds, die temperatures,to predict defects such as porosity or cold shuts. Real-time alerts help operators adjust parameters before issues arise.



By learning from thousands of historical production cycles, ML systems identify patterns that may lead to part failures or quality deviations. These tools allow operators to act preemptively,modifying die temperature, shot velocity, or plunger positions,before a non-conforming part is made. This also enhances traceability, helping quality engineers to document process parameters that caused or avoided a defect.

2. Process Optimization with AI-integrated Machinery

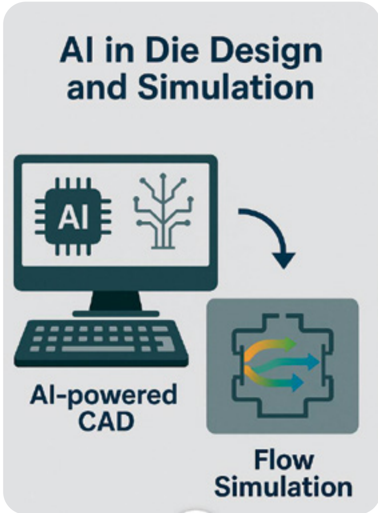
Modern HPDC machines equipped with AI modules can auto-correct plunger profiles, cooling cycles, and vent actuation based on each shot. Pattern-recognition tools can also flag anomalies invisible to the human eye.



AI modules now provide actionable insights directly on machine HMIs (Human Machine Interfaces), recommending optimal machine settings based on prior performance. This reduces overdependence on skilled operators and brings uniformity across shifts. These optimizations improve die thermal balance, reduce vent chokes, and result in consistent shot-to-shot repeatability, ultimately reducing machine downtime.

3. AI in Die Design and Simulation

AI-powered CAD tools generate optimized runner/gate designs, simulate flow characteristics, and recommend changes to reduce turbulence or hotspots, before steel is cut.



In the traditional design approach, die development involved multiple iterations and costly trials. AI-powered design platforms now help die designers experiment with geometry, wall thickness, vent locations, and overflow positions using predictive modeling. This early feedback loop improves manufacturability and reduces tooling rework, allowing faster progression from concept to casting.

4. Energy Management and Sustainability

AI monitors energy use in furnaces, compressors, and hydraulics, identifying overconsumption and optimizing load distribution. This supports cost reduction and ESG compliance.

Power consumption contributes significantly to operating costs in aluminium foundries. AI systems track energy use not just at machine level but across zones,furnace, hydraulics, compressors, and lighting. These insights enable scheduling energy-heavy operations during off-peak tariff hours and improving furnace idle-time efficiency, thereby contributing to both cost and environmental goals.

5. Smart Scheduling and Inventory Management

ML enables dynamic production scheduling by analyzing demand patterns, tooling readiness, and material availability. AI prevents overproduction and streamlines raw material procurement.

AI brings agility to production planning by syncing sales forecasts, tool readiness, and WIP inventory. For instance, it can reprioritize batches based on urgent customer needs or adjust output when tool breakdowns occur. By connecting shopfloor execution to enterprise planning, it enables dynamic decision-making and lowers the risk of underutilization or overstocking.

6. Human-AI Collaboration and Knowledge Retention
AI tools assist in training new operators, simulate rare scenarios, and preserve expert knowledge through AR-based support and interactive SOPs.

With workforce challenges and increasing automation, preserving institutional knowledge is crucial. AI tools, combined with AR/VR platforms, enable immersive training modules that replicate real-life casting scenarios. These tools allow a new generation of foundry professionals to learn hands-on without expensive trial-and-error, preserving the tacit wisdom of retiring experts.

CONCLUSION: EMBRACING THE INTELLIGENT FOUNDRY

The adoption of AI and ML is not about replacing the human factor; it's about augmenting expertise with intelligence. From predictive quality to sustainable operations, these technologies offer foundries the edge they need in a highly competitive, precision-driven market.

For members of Alucast and stakeholders in the die casting value chain, now is the time to invest in digital infrastructure, cross-train teams, and collaborate with technology partners. Because in the future, aluminium die casting won't just be about molten metal...it will be about smart decisions, made in milliseconds.

Happy die casting!

G. Praburam
Managing Partner
Alubee Diecasters, Hosur

Contribute Articles for ALUCAST Journal - Themes for the year 2025

August 2025	**Aluminium Alloys and Metal Treatments for Critical Castings**
October 2025	**Recent Developments in Casting Techniques and Equipments**
December 2025	**ALUCAST 2025 Special**

Please email your articles to: alucastindia@alucast.co.in

Summary Report: Cumulative Production, Domestic Sales & Exports data for the period of April - March 2025									
Report I - Number of Vehicles									
Category	Production			Domestic Sales			Exports		
Segment/Subsegment	April - March			April - March			April - March		
	2023-2024	2024-2025	% Change	2023-2024	2024-2025	% Change	2023-2024	2024-2025	% Change
Passenger Vehicles (PVs)*									
Passenger Cars	19,79,907	17,49,506	-11.6%	15,48,947	13,53,287	-12.6%	4,29,677	3,98,879	-7.2%
Utility Vehicles(UVs)	27,77,051	31,55,312	13.6%	25,20,691	27,97,229	11.0%	2,34,720	3,62,160	54.3%
Vans	1,44,882	1,56,346	7.9%	1,49,112	1,51,332	1.5%	7,708	9,325	21.0%
Total Passenger Vehicles (PVs)	**49,01,840**	**50,61,164**	**3.3%**	**42,18,750**	**43,01,848**	**2.0%**	**6,72,105**	**7,70,364**	**14.6%**
Commercial Vehicles (CVs) - M & HCVs									
Passenger Carrier	55,744	70,178	25.9%	53,768	66,328	23.4%	10,014	11,236	12.2%
Goods Carrier	3,37,719	3,23,441	-4.2%	3,20,244	3,07,491	-4.0%	8,211	12,015	46.3%
Total M&HCVs	**3,93,463**	**3,93,619**	**0.0%**	**3,74,012**	**3,73,819**	**-0.1%**	**18,225**	**23,251**	**27.6%**
Commercial Vehicles (CVs) - LCVs									
Passenger Carrier	73,229	65,550	-10.5%	51,750	54,807	5.9%	3,631	4,889	34.6%
Goods Carrier	6,00,812	5,73,476	-4.5%	5,43,008	5,28,045	-2.8%	43,962	52,846	20.2%
Total LCVs	**6,74,041**	**6,39,026**	**-5.2%**	**5,94,758**	**5,82,852**	**-2.0%**	**47,593**	**57,735**	**21.3%**
Total Commercial Vehicles (CVs)	**10,67,504**	**10,32,645**	**-3.3%**	**9,68,770**	**9,56,671**	**-1.2%**	**65,818**	**80,986**	**23.0%**
Three Wheelers									
Passenger Carrier	8,46,385	9,05,821	7.0%	5,48,090	6,01,642	9.8%	2,96,080	3,03,141	2.4%
Goods Carrier	1,16,141	1,21,195	4.4%	1,11,519	1,17,156	5.1%	3,897	3,739	-4.1%
E-Rickshaw	29,830	18,715	-37.3%	31,290	18,474	-41.0%	-	34	-
E-Cart	3,803	4,289	12.8%	3,902	4,148	6.3%	-	-	-
Total Three Wheelers	**9,96,159**	**10,50,020**	**5.4%**	**6,94,801**	**7,41,420**	**6.7%**	**2,99,977**	**3,06,914**	**2.3%**
Two Wheelers									
Scooter/ Scooterettee	63,91,272	74,37,681	16.4%	58,39,325	68,53,214	17.4%	5,12,347	5,69,093	11.1%
Motorcycle/Step-Throughs	1,45,89,393	1,59,22,027	9.1%	1,16,53,237	1,22,52,305	5.1%	29,43,341	36,20,886	23.0%
Mopeds	4,87,862	5,24,149	7.4%	4,81,803	5,01,813	4.2%	2,728	8,424	208.8%
Total Two Wheelers	**2,14,68,527**	**2,38,83,857**	**11.3%**	**1,79,74,365**	**1,96,07,332**	**9.1%**	**34,58,416**	**41,98,403**	**21.4%**
Quadricycle									
Quadricycle	5,006	6,488	29.6%	725	120	-83.4%	4,178	6,422	53.7%
Grand Total of All Categories	**2,84,39,036**	**3,10,34,174**	**9.1%**	**2,38,57,411**	**2,56,07,391**	**7.3%**	**45,00,494**	**53,63,089**	**19.2%**

*** BMW, Mercedes, JLR and Volvo Auto data are not available. ** Daimler & JBM data are not available. Society of Indian Automobile Manufacturers (15/04/2025)**

Summary Report: Cumulative Production, Domestic Sales & Exports data for the month of April 2025									
Report I - Number of Vehicles									
Category	Production			Domestic Sales			Exports		
Segment/Subsegment	April			April			April		
	2024	2025	% Change	2024	2025	% Change	2024	2025	% Change
Passenger Vehicles (PVs)*									
Passenger Cars	1,31,846	1,35,819	3.0%	96,357	91,148	-5.4%	30,268	27,947	-7.7%
Utility Vehicles(UVs)	2,06,585	2,41,529	16.9%	1,79,329	2,01,062	12.1%	19,022	31,115	63.6%
Vans	12,859	11,854	-7.8%	12,060	11,438	-5.2%	273	333	22.0%
Total Passenger Vehicles (PVs)	**3,51,290**	**3,89,202**	**10.8%**	**2,87,746**	**3,03,648**	**5.5%**	**49,563**	**59,395**	**19.8%**
Three Wheelers									
Passenger Carrier	62,182	67,252	8.2%	39,383	40,167	2.0%	22,359	27,278	22.0%
Goods Carrier	9,758	8,513	-12.8%	8,818	8,135	-7.7%	122	246	101.6%
E-Rickshaw	1,350	571	-57.7%	1,308	830	-36.5%	-	-	-
E-Cart	289	267	-7.6%	265	309	16.6%	-	-	-
Total Three Wheelers	**73,579**	**76,603**	**4.1%**	**49,774**	**49,441**	**-0.7%**	**22,481**	**27,524**	**22.4%**
Two Wheelers									
Scooter/ Scooterettee	5,94,694	6,48,633	9.1%	5,81,277	5,48,370	-5.7%	65,874	53,879	-18.2%
Motorcycle/Step-Throughs	12,98,063	11,66,462	-10.1%	11,28,192	8,71,666	-22.7%	2,54,744	3,13,008	22.9%
Mopeds	40,229	37,771	-6.1%	41,924	38,748	-7.6%	432	1,314	204.2%
Total Two Wheelers	**19,32,986**	**18,52,866**	**-4.1%**	**17,51,393**	**14,58,784**	**-16.7%**	**3,21,050**	**3,68,201**	**14.7%**
Quadricycle									
Quadricycle	756	211	-72.1%	19	3	-84.2%	664	210	-68.4%
Grand Total of All Categories	**23,58,611**	**23,18,882**	**-1.7%**	**20,88,932**	**18,11,876**	**-13.3%**	**3,93,758**	**4,55,330**	**15.6%**

*** BMW, Mercedes,JLR, Tata Motors and Volvo Auto data is not available. Society of Indian Automobile Manufacturers (15/05/2025)**

Use of AI and Machine Learning in Aluminium Die Casting

BÜHLER Page

INTRODUCTION

The die casting industry is experiencing a paradigm shift as digitalization and data-driven innovations take center stage. Worldwide, foundries face mounting pressure to increase quality, efficiency and uptime while navigating complex challenges such as skill shortages and rising cost pressures.

Artificial Intelligence (AI) and Machine Learning are now emerging as transformative enablers, empowering die casters to make faster, more informed decisions, predict issues before they occur and ensure part quality with unprecedented consistency.

BÜHLER'S DIGITAL JOURNEY – BÜHLER INSIGHTS

At Bühler, we are shaping this digital transformation with our robust, cloud-based platform Bühler Insights. Our digital service platform is designed to provide actionable intelligence to foundries, with three powerful tools at its core:

Dashboards

Real-time visualization of machine and equipment status, KPIs and instantaneous alarms. This delivers plant-wide transparency, allowing teams to react quickly and prevent costly downtime.

Analytics

Focused on actionable optimization, this suite includes two sub-products:

- Downtime Analysis: Detailed breakdown of every stoppage event, comprehensive listings of warnings and alarms and root-cause analytics to drive up availability and enable 24/7 operation.
- Process Analytics: Delivers a holistic performance overview, monitors die program changes, records parameter changes and provides full traceability linking process settings to individual part quality.

Reporting

Automatic, tailored reports bring production, technology, maintenance and management teams together. These reports enable monthly reviews, effective daily meetings, and seamless shift handovers—all based on objective, up-to-date data. This integrated ecosystem is purpose-built to lay the foundation for advanced AI development: only with robust data can true machine learning and AI applications flourish.

Harnessing AI for the Foundry of the Future

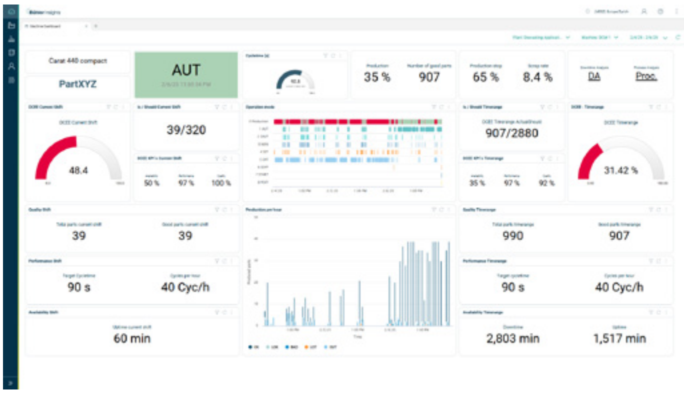
The integration of AI and machine learning in aluminum die casting delivers significant advantages for foundries. AI has the potential to revolutionize aluminum die casting by driving the industry toward more intelligent and autonomous production. One of the most promising applications is predictive quality, where AI algorithms analyze process data in real-time to forecast part quality immediately after each cycle.

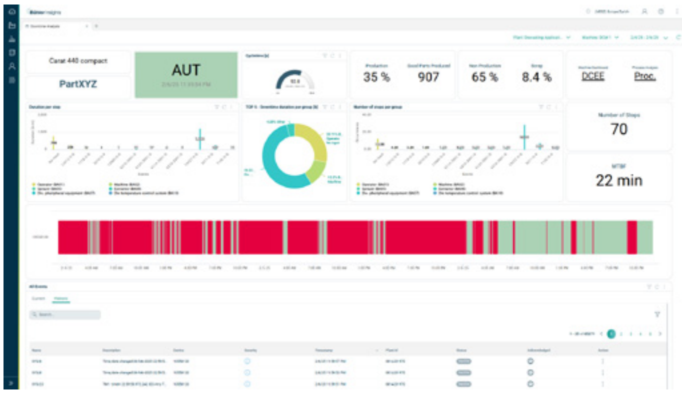
This enables a significant reduction in scrap rates, minimizes the reliance on manual/automatic part inspections and opens the door to automated recommendations for process parameters. The long-term vision is a fully self- optimizing production environment where machines can continuously regulate themselves for optimal performance.

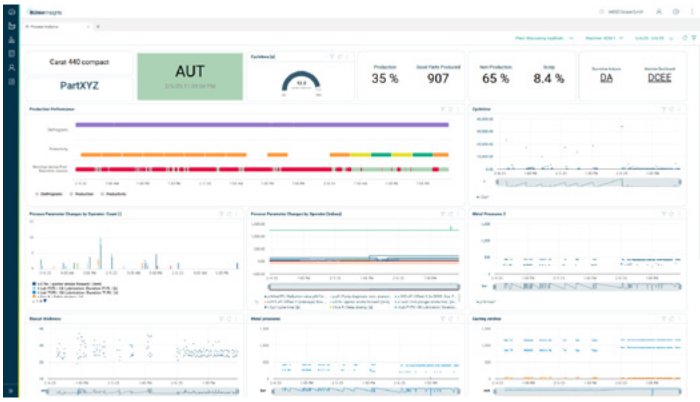
Another key area is predictive maintenance. Here, machine learning models monitor equipment data to predict when specific components are likely to require maintenance or replacement.

Instead of relying solely on fixed maintenance intervals or reacting to unexpected failures, predictive maintenance enables alarms and interventions before breakdowns occur. This proactive approach helps to maximize machine uptime, reduce maintenance costs and increase reliability, paving the way for near-continuous manufacturing in the foundry of the future.

Screenshots Bühler Insights:







For more information: die-casting@buhlergroup.com

ALUCAST SNIPPETS

HERO EXPECTS TWO-WHEELER INDUSTRY TO GROW 6–7% IN FY26; AIMS TO OUTPACE SECTOR

Company management is optimistic about domestic demand due to favourable macroeconomic factors, expectations of a better monsoon, and strong wedding season demand.

Hero MotoCorp Ltd expects the Indian two-wheeler industry's sales to grow by 6–7% in the financial year 2025–26, on the back of favourable macroeconomic factors, expectations of a better monsoon, and strong wedding season demand. The company, however, is confident of outpacing the industry, backed by new product launches and improvements in entry-level and 125cc two-wheeler sales.

"While there is ongoing global turmoil due to the border situation and trade tensions, on the domestic front, the economy has started on a positive note, driven by tapering inflation, lower interest rates, income tax cuts, and expectations of a better monsoon," said Vikram Kasbekar, Acting Chief Executive Officer, during an analyst call following the company's FY25 earnings announcement.

"With regard to the two-wheeler industry riding on the wave of positive economic momentum, demand is shaping up nicely, boosted particularly by a strong marriage season in May and June," he added.

Ashutosh Varma, Chief Business Officer of Hero MotoCorp's India Business Unit, echoed the optimism and pegged industry growth in the 6–7% range for the current fiscal. He expressed confidence that Hero would outperform this benchmark.

"We have some launches that happened in Q4 which are yet to fully manifest in terms of volumes," said Varma. "The confidence comes from the delivery we had in Q4. In the entry category, we gained 600 basis points in market share. Over the year, we recovered strongly in the 125cc category, gaining 250 basis points. The new scooters we've launched have met with an amazing response, leading to increased market share and retail growth late in Q4."

"We are also working, as industry leaders, on the core category. Our work is to expand the category. The fact that we have 1 lakh customers reporting into our workshops every day gives us an excellent opportunity to work on upgrades and owned-based marketing. These are fundamental strengths that we will increasingly leverage this year, and we are very confident this will help us gain market share and outpace industry growth," the chief business officer said.

On rural demand, company executives noted that recovery was already underway and would likely strengthen with the expected monsoon, a strong marriage season, government spending in rural areas, and lower inflation.

Hero's global business is also expected to see a boost. "Our strategy of developing country-specific products for markets like LATAM, Bangladesh, and Nigeria is paying off," said Kasbekar. "We've re-entered Nepal and expanded into Sri Lanka and the Philippines, which will meaningfully contribute to growth in FY26. We are confident of gaining global market share this year."

In FY25, Hero MotoCorp reported total sales of 5.9 million units, including 5.61 million units in domestic sales and 287,429 units in exports. While domestic sales grew 4%, exports surged by 43% year-on-year. According to data from SIAM, total industry two-wheeler dispatches rose 9.1% to 19.61 million units in FY25. Retail sales, as per FADA, grew 7.1% to 18.88 million units, driven by rural recovery and rising consumer confidence.

Recently, another two-wheeler maker, TVS Motor Co Ltd, also said it expects the sales momentum seen in FY25 to continue in both domestic and international markets in the ongoing financial year, with the company aiming to outperform overall industry growth in both markets.

Growth Strategy

Looking ahead, Hero plans to continue investing aggressively in premium motorcycles, scooters, and its EV portfolio. "We remain consistent in our commitment to growth. We are investing in premium, scooters, and EVs, and also improving customer experience in stores through Hero 2.0 and our Premia offerings," said Vivek Anand, Chief Financial Officer.

Anand also emphasized Hero's strategy of expanding into adjacent mobility categories. "This quarter, we acquired a 34.1% stake in Euler Motors for â‚¹510 crore, marking our entry into the fast-growing electric three-wheeler segment," he said.

"We are positive about the growth prospects of the two-wheeler industry. With steady demand, recovery in both rural and urban markets, ramp-up of the 125cc portfolio, new launches, and continued brand investments, we expect to grow ahead of the industry," he added.

TATA MOTORS SEES BRIGHTER FY26 FOR CV, PV SEGMENTS; AWAITS TARIFF CLARITY

US-UK trade agreement offers partial respite, but fine print remains crucial for JLR strategy, according to Group CFO Balaji. Tata Motors Ltd is optimistic about delivering better sales and earnings from its passenger vehicle (PV) and commercial vehicle (CV) businesses in FY26, but lacks clarity on Jaguar Land Rover (JLR) due to ongoing global tariff developments, Group CFO PB Balaji said on Tuesday.

"We can give you better numbers as far as CV and PV are concerned. But for JLR, we need more clarity on how the tariffs will play out," Balaji said at a press conference to discuss the company's FY25 financial performance. JLR's short-term prospects are clouded by evolving global trade dynamics, particularly in the US market. In April, the automaker implemented a series of interim measures to mitigate the impact of steep US tariffs on UK-made auto exports, which led JLR to halt shipments to the US in April.

"As far as JLR is concerned, there are just too many moving parts and we will have to wait till the more clarity emerges on the tariff side, in terms of how it is going to get treated. So therefore, let's just wait for the investor day on 16th of June, where we'll be able to give you a better update," Balaji said.

The Tata Group company welcomed the recent US-UK trade agreement, which reduces US tariffs on UK vehicle imports from 27.5% to 10%, within an annual quota of 100,000 vehicles. While this brings partial relief, the new rate remains significantly above the earlier 2.5%, pushing JLR to pursue cost-efficiency initiatives."We welcome the development. It's directionally on the right track and certainly a better situation than we faced earlier. However, we're awaiting the fine print, especially on timing, applicability, and whether it extends to parts and accessories. We expect formal notifications and clarifications in the coming days, including whether the change will be applied retrospectively," Balaji said. On the investments in JLR, the company expects spends to remain at £18 billion over a five year period, and the investment will be funded by operational cash flows.

PV and CV Segments

Balaji expects the CV and PV segments to perform better than last year, driven by improved market conditions, innovation, and an exciting product pipeline. "Next year is expected to be a year of growth, margin improvement, and market share gains in passenger vehicles," he said, highlighting significant EV growth as well.

Obituary

Mr. Manoj Sharma

(23rd February 1959 – 28th April 2025)

Director - Allcast Technologies Limited
Founder - Allcast Metals Pvt. Ltd.

He was a member of ALUCAST and an ex-secretary of the North Zonal Centre of ALUCAST.

May God grant his soul eternal rest and give his family and loved ones strength to bear this irreparable loss.