INAE

TechFrontier

Volume I | Issue III | December 2025

Thematic Articles on Cyber-Physical Systems

Scaling the Impact of Cyber-Physical Systems – A Business View

Everything with AI: Intelligent Connected Manufacturing for Next-Generation Industrial Cyber-Physical Systems

Industrial Cyber-Physical Systems Over Wireless

Artificial Intelligence Deployment in Metallurgical Industries

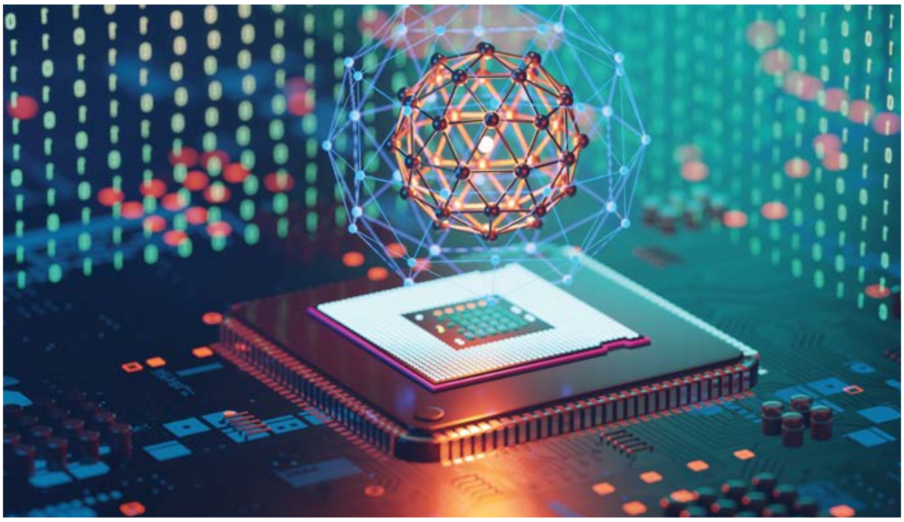
Indian National Academy of Engineering

Indian National Academy of Engineering

*Ground Floor, Block-II, Technology Bhavan,
New Mehrauli Road, New Delhi-110016 (India)
Ph. +91 11 26582475 email: inaehq@inae.in*

Contents

Volume I | Issue III
December 2025



Featured Articles

Prof. Amit Agrawal, FNAE, is Institute Chair Professor, Dept. of Mechanical Engineering, IIT Bombay. His research interests lie in Fluid Mechanics and Heat Transfer using experimental, theoretical and simulations tools. He was awarded the Shanti Swarup Bhatnagar Prize for Science and Technology for his contributions to engineering sciences in 2018.

Editorial Desk

We are pleased to share with you the latest edition of INAE TechFrontier, the quarterly e-magazine of the Indian National Academy of Engineering (INAE). The first volume on Quantum Technology successfully was launched this year on April 20, 2025, during the INAE Foundation Day, the magazine continues to serve as a platform for showcasing recent advancements and innovations across the engineering and technology landscape.

This edition focuses on the theme of **Cyber-Physical Systems**, a rapidly evolving domain that integrates computation, communication, and control to transform sectors ranging from manufacturing to healthcare, transportation, and industrial automation. The curated articles in this issue offer diverse perspectives on how Cyber-Physical Systems are reshaping industries, enabling intelligent systems, and driving next-generation engineering solutions.

The lead article explores the strategic and economic dimensions of CPS, highlighting how businesses can leverage these technologies to enhance productivity, unlock new value chains, and accelerate digital transformation. Another article focusses on the convergence of Artificial Intelligence and Cyber-Physical Systems, this piece delves into how intelligent, connected manufacturing ecosystems are enabling smarter decision-making, adaptive operations, and enhanced system resilience.

The third contribution provides insights into the application of AI within metallurgical processes, emphasizing how data-driven intelligence and CPS frameworks are improving efficiency, safety, and process optimization. The final article addresses the critical role of communication technologies, this contribution examines wireless solutions for industrial CPS, discussing challenges, architectures, and innovations that enable flexible, scalable, and reliable industrial operations.

The next issue, due in March 2026, shall focus on the ***Sustainability of Civil Infrastructure***. We are actively inviting engaging and original articles from interested contributors. Submissions may be sent to *publications@inae.in.*

Prof. Amit Agrawal
FNAE, Vice-President (Publications), INAE

Mr. K Ananth Krishnan

Mr. K Ananth Krishnan, FNAE, retired as the Chief Technology Officer of Tata Consultancy Services after a career of over three and a half decades in the same organisation. In this role, he was responsible for Research, Innovation and Co-Innovation. His areas of expertise include the Management of Technology and Inter-Disciplinary Applications of Computer Science and Engineering.

Ananth has served on the Governing Council of INAE and other Academic Institutions, Industry Advisory Boards, and Government Committees. He was a regular invitee to the Board of TCS and is serving as independent director of TVS Supply Chain Solutions.

Scaling the Impact of Cyber-Physical Systems – A Business View

Mr. K Ananth Krishnan, FNAE, Former Chief Technology Officer of Tata Consultancy Services

Abstract

This paper highlights the business challenges and potential approaches for implementing Cyber-Physical Systems at scale. Such systems are inherently inter-disciplinary from a Research and Innovation perspective. The opportunities to implement such systems span across organisation boundaries and even industry boundaries. These factors significantly increase the complexity, costs and time of taking initial ideas to full scale implementation.

Individual enterprises and national initiatives are tackling these challenges with innovative methods and practices. The software industry in India, is systematically applying methods and techniques to scale the impact of Research, Innovation and Implementation. We describe some of these techniques in the context of Cyber-Physical Systems. We conclude with an overview of a novel set of approaches being adopted by a National Mission established by the Department of Science and Technology, Government of India.

Introduction

The Cyber-Physical Systems Summit held in the United States in 2006 was a pivotal event in the recognition of Cyber-Physical Systems as a new opportunity for not just advancing Science and Technology but also creating significant impact for all of humanity. It led to the publication of the Cyber-Physical Systems White Paper[1]. This led to subsequent progress in many areas of Research and Innovation related to the discipline[2], especially the ability to monitor, infer, control, and optimise operations at the intersection of computational elements, network elements, physical elements and external processes.

The inter-disciplinary nature of Cyber-Physical Systems is evident at multiple levels. For example, such systems include physical devices, sensors, and actuators for a wide range of application domains (agriculture, mining, metallurgy, manufacturing, transportation and healthcare to name a few). An equally diverse set of technology domains use Cyber-Physical Systems: industrial automation, telecommunications, aerospace, materials and structures, life sciences are among the examples. At the level of inferencing, decision making and control, Cyber-Physical Systems could involve Control Systems, Big Data, Artificial Intelligence (AI) and Machine Learning, Robotics and Autonomous Systems. Applications areas include Additive Manufacturing, Computer Vision and Speech, Collaborative Robotics and Digital Twins to add meaningful value to the end user.

Given this depth and range of diversity and inter-disciplinary possibilities, let us now move to a business or even a societal perspective. *What would the world look like in 2050? What will be the expectations from Cyber-Physical Systems?*

There are a number of 'Grand Challenges' of planetary scale, starting with sustainability and climate change, to food, education, skills, livelihood, shelter, health and well being. Tackling these requires significant invention, innovation, collaboration, and a commitment to making the world a better place for us and future generations. We will need a widespread capability to transform novel ideas and concepts in not just Cyber-Physical Systems but a range of other disciplines into a stream of new products, services and business models at an ever-increasing pace.

Platforms like the World Wide Web and its multiple avatars, optical fibre and radio technologies, connected devices, sensors, mobile devices and the AI revolution have created an abundance of compute, data and connectivity to lay the foundations for Cyber-Physical Systems. There is of course an increased need for trust and governance, underpinned by security and privacy for each entity in the digitally connected world. Accessibility and inclusiveness of technology for each part of the world becomes even more important.

It is clear that we live in a world that has increasing expectations from technology. We have come to expect an inexhaustible series of inventions, and the innovations that arise from these inventions, at an ever-increasing rate. Researchers, technologists, engineers and business leaders have an enormous responsibility in living up to these expectations.

The Technology-Market Map

How will these researchers, technologists, engineers and business leaders respond? The outcomes they produce will need to be applied towards the common good, across multiple industries, ecosystems and value streams, and will be called upon to solve our largest and most complex challenges.

There are many ways to establish, communicate and manage such a rich agenda for Research, Innovation and Implementation. We now describe a set of methods and process based on the work done by the late Prof. Clayton M Christensen of Harvard Business School[3,4,5] which were deployed in Tata Consultancy Services when he was an independent director on the board. It is called the 'Clay Map' in his memory and is based on the much more detailed 'Technology Market Map' he has described in his research and publications.

The key concept of a Clay Map is to provide basis for a differentiated approach to a large number of innovation ideas in the portfolio and executing multiple types of ideas and innovations in a systematic manner. The Clay Map as a mental model has 4 categories for operating the ideas to implementation process based on a 2x2 classification.

The horizontal axis addresses the 'jobs to be done' and starts with questions like 'why do my customers use my product or my service today?' followed by 'how could this change in the future'. The vertical axis is the 'capability required for implementing these jobs' and starts with questions like 'what capabilities do I have today (e.g., technology, talent, business model, capital, intellectual property)' followed by 'what capabilities do I need for the future'.

The 4 quadrants of the Clay Map can be used by an enterprise for classifying a set of Innovation ideas, and then developing an execution model to go from ideas to implementation:

1. Current capabilities to address current jobs to be done

- Ideas which innovate with current or incrementally improved capabilities and address current market and customer needs.
- These ideas could be around efficiency, scale, compliance and resilience by applying Cyber-Physical Systems at the core of the current business with current customers.
- These drive necessary, incremental or derivative improvements in current products and services.
- The risk of failure is relatively low, and timelines to deliver impact are usually a few weeks to a few months.
- Such ideas are best owned and implemented by teams on the ground in each business.
- Examples:
  - Improve the reliability of equipment by enabling sensor-based predictive maintenance.
  - Improve the resilience of crops with targeted detection and elimination of pests.
  - Improve the health of a diabetic patient with a wearable blood sugar sensor.

2. New capabilities to address current jobs to be done

- Technology-led

Opportunities for large improvements in current products and services.

- The risk is moderate to high, but timelines could be in months to years.
- Such ideas are best owned by specialists from Research and Innovation teams in partnership with the new product/service development capability deployed by each business.
- Examples:
  - Deliver on the business promise of 5G, industry 4.0 and similar frameworks at scale.
  - Improve the safety features of a car starting with advanced driver assistance systems and moving to fully autonomous automobiles.
  - Radically transform the capability for elderly care with autonomous robotic healthcare and other advanced assistive care technologies.

3. Current capabilities to address future jobs to be done

- Market creating opportunities that use current or incrementally improved capabilities to address future customer needs or futuristic markets.
- Could involve collaboration between engineering and business school researchers for arriving at new business models for existing capabilities or new market adaptations of current products and services.
- Inside an enterprise, this could be driven by the new product/service development, and a business incubation team, perhaps with ecosystem partners.
- The risk is moderate to high, but timelines could be in months to years.
- Examples:
  - Create 'shared' or 'fractional' or 'as-a-service' models for appliances, equipment or instruments based on sensor-based resource allocation.
  - Create new markets for insuring 'high-risk' categories like very young or very old drivers, with sensor-based measurements and automated driver assistance technologies.
  - Enable new retailing models like 10-minute delivery and unmanned self-service stores using robotic warehouses, intelligent shelves and automated checkouts.

4. New capabilities to address future jobs to be done

- Blue-sky opportunities, based on radical new capabilities to address future customer needs or futuristic markets, or new business models. These will typically use radical technology with leapfrog business models for future products and services.
- This is best driven in a research-led manner and iterated between academia, industry, startups and government funding.
- The risk is high, and timelines could be in years.
- Examples:
  - Ideation on advancements in other areas of computing and engineering like Artificial General Intelligence (AGI), Quantum Computing, 6G and beyond, Meta Materials and so on create new opportunities.
  - Visualisation of next generation defense and warfare risks, and mitigation of these.
  - Challenges and opportunities from space and interplanetary travel.

The most common use of the four quadrants of the Clay Map, is to visually represent different ideas and projects comprising the agenda for research and innovation. At the next step, the method can be used for resource allocation and to set expectations for the kind of approaches and outcomes being aimed for. Each of the quadrants has a different portfolio of ideas, different execution teams, different ecosystem partnerships, different timelines, different risk and return profiles. A given enterprise will take decisions on which quadrants will be appropriate for their context. The organisation (or nation) will also allocate resources appropriate to its needs and context.

As an example, a resource allocation of (100,0,0,0) definitely minimises risk of failures but is unlikely to make substantial progress in terms of impact. At the other extreme, (0,0,0,100) will be very visionary and exciting but is unlikely to make any impact for several years.

The 4E Model

The definition and depiction of a strategy in the form of a Clay Map is the first step in the transformation of an idea or concept into a market winning product, service or business model. The complexity of this process is higher in Cyber-Physical Systems, as we noted earlier because of the need for multiple disciplines and stakeholders to come together. Clearly, an enterprise of any size will have to apply an agile, responsive and adaptable process to get consistent results. While many such processes have been described [6,7,8] a specific example is the 4E model adopted by Tata Consultancy Services for executing their Research and Innovation agenda[9].

The 4E model is so named for the Four Capabilities mapping into Four Phases required to operate it:

A. Evangelist-Entrepreneur

B. Explore

C. Enable-Engineer

D. Exploit

The enterprise needs a mindset like a venture capital team, with a fund raised from internal or external investors, and a large number of passionate 'startups' which have ideas in each quadrant of the Clay Map. Each of these ideas will come to life in a series of 90-day 'agile' sprints.

The first one or two sprints, with a relatively small budget (like a 'seed' or 'angel', fund), will operate with the 'Explore' mindset. The idea, its market, its technology and its commercial model will be designed and built as a laboratory prototype with a tailored, initial version of the business model canvas. The Evangelist-Entrepreneur plays a crucial leadership role in this crucial phase working with the necessary mix of people with research, technology, engineering capabilities.

If the prototype and related business artefacts (the 'Minimum Viable Product[10]') are found to be satisfactory, the idea earns some more time and resources and moves to the 'Engineer-Enable' mindset. The goal is to go from a prototype to something which is ready for the market. The same Evangelist-Entrepreneur should lead the team with more business, technology and engineering capabilities. The following 90-day sprints will deliver engineered, well-designed artefacts, actual customer and market trials, validation of the starting hypotheses, and a financial plus risk model.

At this stage, the enterprise will make the hard choices of which ideas will go into the last phase, where the mindset will be to 'Exploit' the full potential of each idea and realise the outcomes at scale. The entire business will be fully engaged in the sprints in this phase, and they will work with the Evangelist-Entrepreneur with large investments into a series of sprints to scale the right ideas. The 'startup' will either grow on its own under their care or may be 'acquired' or 'merged' by an existing business.

These 4E mindsets and capabilities – Explore, Engineer-Enable, Exploit and Evangelist-Entrepreneur are equally important. An individual will likely be a specialist in only one of these at a given time and may be part of one particular project sprint. Over a period of time, the depth of experience in the area of specialisation will be supplemented by width of exposure to the other skill sets. The individual can then choose to switch from one to the other as part of their career journeys.

Let us look at the 4E model in operation through a quadrant 1 example: Plant Automation in Manufacturing. Here, the idea aims to leverage Advanced AI and Computer Vision for improving the efficiency of operations in a manufacturing plant. It is sponsored by the head of Plant Operations, and the 'Evangelist-Entrepreneur' is the executive assistant to the sponsor, a fresh MBA from a leading business school. The idea has been placed in quadrant 1 since the aspiration is to achieve small gains in the core of the current business. Plant Operations is at the heart of manufacturing, and any Improvement to quality, cost, throughput, time and safety are very welcome to the business. While the goals are modest and incremental, the means to the goals include AI and Computer Vision, both very complex and advanced technologies.

Let's see what the team is likely to do in the Explore phase and at the first review.

The team will be well served if they identify a pipeline of problems in the Plant Automation space, which can be addressed by available AI and Computer Vision solutions. The priority in quadrant 1 is to identify the right problems, identify risks and path to value, quick deployment and to embed the outcomes into the core business.

The team is likely to describe their status with statements like 'here is a problem which is challenging the throughput and quality in our main assembly line. Our prototype has been built with a combination of technologies which are already available from partners or built in-house. We are seeing 2% improvements in throughput and 4% reduction in our primary defects. No major risks are foreseen with the deployment. Our cost to develop and deploy the prototype versus the benefit in terms of savings is attractive. We seek approval to validate these results and scale these prototypes to production'.

It will not be surprising if the Engineer-Enable stage for this idea is executed by the core of a future 'Center of Excellence, or CoE'. The one or few prototypes will be the first of many problems in Plant Automation which will benefit from the application of advanced technology. The 'Engineer-Enable' team will need to lay the foundations for this. The obvious 'deliverable' will be to 'go-live' with the final versions of the prototypes.

This go-live process by itself will have robust checklists for quality, risk, reliability, scalability, serviceability, security and so on. The benefit case is equally important – when does the cost of deploying the innovative new technologies start paying back in the actual business.

Since quadrant 1 is largely internally focused, the Engineer-Enable to Exploit transition will be fairly straightforward. It will ask questions on the 'go-live' steps for each project but also address the larger challenge of embedding the innovative ideas into the core business capabilities of the organisation. As we remarked a few minutes ago a new or existing Center of Excellence could be the capability 'home' to own this for the business. It will also be useful to carry out a 'freedom to operate' analysis of the intellectual property created and used for each solution. The risk of an IP infringement lurking in the core processes of the manufacturing line is not small and can be mitigated by either licensing or by other IP arrangements. The effect of disclosure of the efficiencies and other benefits of a purely internal nature will need to be examined as well. The publicity and 'talk value' of the innovation could focus on the 'what has been achieved', rather than the 'how was it done'.

This example shows how the 4E model is an adaptation of many different ways of starting with a nebulous idea and delivering value as an outcome. There are some similarities with the Technology Readiness Level (TRL) model[11] in that Explore could be mapped to TRL 1-3, Engineer-Enable to TRL 4-6 and Exploit to TRL 7-9. The agile model is used to build in iterations and active stakeholder engagement especially with customers (current or future) and partners at all stages. This engagement, especially in the early stages, helps validate assumptions, another critical success factor for any project.

Examples of Country-Wide Missions

The scope of applicability of Cyber-Physical Systems is much more than just a single enterprise. It could indeed be global[12], or at a country level.

The vision for Society 5.0 vision of Japan as a country is illustrated as follows[13]:

"The vision of the future society that Japan should strive towards that follows the eras of the hunting society (Society 1.0), agricultural society (Society 2.0), industrial society (Society 3.0), and information society (Society 4.0). In the 5th Science and Technology Basic Plan (Cabinet decision of January 22, 2016) (Society 5.0) was first proposed as a human-centered society in which economic development and the resolution of social issues are compatible with each other through a highly integrated system of cyberspace and physical space."

India has also established a National Mission on Interdisciplinary Cyber-Physical Systems[14] under the aegis of the Department of Science and Technology in 2018. Some of the goals of the mission are:

1. Focus on Cyber-Physical Systems (CPS) combining digital/cyber elements with physical objects (e.g. machines, autonomous vehicles) and data with capabilities of communication, data collection & processing, computing, decision making and action.
2. To promote translational research in Cyber-Physical Systems (CPS) and associated technologies.
3. To develop technologies, prototypes and demonstrate associated applications pertaining to national priorities.
4. To enhance high-end researchers base, Human Resource Development (HRD) and skill-sets in these emerging areas.
5. To enhance core competencies, capacity building and training to nurture innovation and start-up ecosystem.
6. To establish and strengthen the international collaborative research for cross-fertilization of ideas.
7. To set up world-class interdisciplinary centers of excellence (Technology Innovation Hubs or TIH) in several academic institutions across the country, that can become repositories of core expertise in CPS and related areas and serve as focal points for technology inputs for the industry and policy advice for the government.
8. To involve Government and Industry R&D labs as partners in the collaboration centers. Incentivise private participation to encourage professional execution and management of pilot scale research projects.
9. To set mission mode application goals and

foundational themes for excellence for different centers. Set up CPS test beds at various centers.

10. To tie up with incubation centers and accelerators to foster close collaboration with entrepreneurship eco-system.
11. To address some of the National issues and development of sector-specific solutions.

The mission is led by an empowered Mission Governing Board (MGB), supported by an Inter-Ministerial Coordination Committee (IMCC) and Scientific Advisory Committee (SAC).

Each TIH is created as a Section-8 Company, an independent entity within the HI. A Tripartite Agreement has been signed by HI, TIH and the Mission Office, DST for all the TIHs. Each TIH is managed by a Hub Governing Board (HGB) chaired by the Director of the HI and members from Academia, Industry and Government. Other academic institutes are connected as SPOKES.

Each TIH creates its own agenda, assembling its own ecosystem capabilities and evolving its execution mechanisms to achieve its goals. A regular cadence of review and experience sharing across the TIH ecosystem supported by third party reviews has also been established. Initial success stories are already emerging and much more is expected.

Conclusions

Cyber-Physical Systems have enormous potential in multiple disciplines, industries and domains. Creating an agenda and traversing the life cycle to implementation is not an easy task for a single enterprise, and more so for nation-wide initiatives. We have described two possible methods in this direction. It is clear that Cyber-Physical Systems will need a lot of Research and Innovation in the areas, as much as the scientific and technological aspects.

References

1. Cyber-Physical Systems and Internet of Things NIST Special Publication 1900-202 *https://nvlpubs.nist.gov/nistpubs/SpecialPublications/NIST.SP.1900-202.pdf*
2. Cyber physical systems, Radhakisan Baheti and Helen Gil *https://ieeecss.org/sites/ieeecss/files/2019-07/IoCT-Part3-02CyberphysicalSystems.pdf*
3. Innovator's Dilemma, Clayton Christensen, *https://www.amazon.in/Innovators-Dilemma-Technologies-Management-Innovation/dp/142219602X*
4. Innovator's Solution, Clayton Christensen, *https://www.amazon.in/Innovators-Solution-Creating-Sustaining-Successful/dp/1422196577*
5. Strategic Management of Technology and Innovation, 5/e, Robert A. Burgelman, Stanford University, Clayton M. Christensen, Harvard Business School, Steven C. Wheelwright, Harvard Bus. Sch. (Emeritus), Brigham Young Univ, *https://highered.mheducation.com/sites/0073381543/information_center_view0/table_of_contents.html*
6. Competing on the edge, Kathleen Eisenhardt and Shauna Brown, *https://www.amazon.com/Competing-Edge-Strategy-Structured-Chaos/dp/0875847544*
7. Winning the right game, Ron Adner, *https://www.amazon.in/Winning-Right-Game-Changing-Management/dp/026204546X*
8. Lean startups, *https://www.startuplessonslearned.com/2008/09/lean-startup.html*
9. Articles on TCS Research and innovation: *https://www.tata.com/newsroom/business/tcs-research-innovation-trddc, https://www.tata.com/newsroom/business/breaking-through-tcs-research-innovation, https://www.tata.com/newsroom/heritage/tcs-research-innovation-trddc-timeline, https://www.tcs.com/who-we-are/tcs-way/article/culture-of-innovation-tcs-building-strong-foundation*
10. Minimum Viable Product, *https://agilealliance.org/glossary/mvp*
11. Technology Readiness Levels, *https://www.nasa.gov/directorates/somd/space-communications-navigation-program/technology-readiness-levels/*
12. The Second Machine Age: Work, Progress (Author, MIT), Andrew McAfee (Author, MIT), *https://wwnorton.com/books/the-second-machine-age/*
13. Society 5.0, *https://www8.cao.go.jp/cstp/english/society5_0/index.html*
14. NMICPS Quarterly Bulletin, April 2025: *https://nmicps.gov.in/BulletinApril2025.pdf*

Everything with AI: Intelligent Connected Manufacturing for Next-Generation Industrial Cyber-Physical Systems

Prof. Sudip Misra, FNAE, INAE Chair Professor in the Department of Computer Science and Engineering, IIT Kharagpur

Kounteya Sarkar, Department of Computer Science and Engineering, IIT Kharagpur

Abstract

The confluence of Artificial Intelligence (AI) and industrial Cyber-Physical Systems (CPS) enables the realization of completely automated industrial processes seeded with due intelligence, which minimizes human intervention as well as human-induced errors. The present state-of-the-art in CPS research involves implementation of AI, including its recent advances, into machineries and their components, controlling systems, monitoring systems. AI also finds applications in another important constituent of CPS – machine-to-machine (M2M) communication. Of special interest in the research community is the development of AI-integrated Programmable Logic Controllers (PLCs), which provide intelligent industrial computing cores and control systems that can monitor CPS parameters, analyze threats and take suitable decisions in real-time. The virtualization of PLC functionalities as software modules and containers enables smooth and efficient AI integration towards further realization of "Intelligent Connected Manufacturing" for next-generation CPS.

Introduction

Rapid advancement of industrial automation has led to the emergence of industrial CPS as the backbone of modern "connected manufacturing" [1]. Such a manufacturing schema entails the heavy use of CPS technologies and related components that connect all minute processes through appropriate networking and communication in such a way that the industry as a whole becomes a singular 'smart entity'. Traditional CPS architectures often face challenges in terms of adaptability, scalability, and decision-making capabilities, particularly with respect to dynamic real-time changes in industrial parameters.

Prof. Sudip Misra

Prof. Sudip Misra, FNAE, is INAE Chair Professor in the Department of Computer Science and Engineering at IIT Kharagpur. His research interests include IoT, communication networks and learning methods. Prof. Misra has published over 550 articles, authored 12 books and won distinguished international awards and accolades. He has served in the Editorial Board of high impactful journals and transactions of IEEE and ACM. He is a Fellow of the ACM, IEEE, NASI, INAE, IET (UK), BCS (UK), RSPH (UK) and IETE, India. He is the Director and Co-Founder of the IoT startup, SensorDrops Networks Private Limited.

Kounteya Sarkar

Kounteya Sarkar is currently serving as Assistant Professor in the Department of Computer Science and Engineering in SRM University AP. He completed his doctoral studies from IIT Kharagpur, where his area of research includes Blockchain, IoT, 6G and quantum computing. He has a B.Sc (Hons.) in Physics from University of Calcutta and Masters in Engineering from BITS Pilani, India. He has published several papers in international transactions and conferences over the years and filed Indian, European and US patents. He received the IEEE Computer Society REM Student Scholarship, Fall 2024 and IEEE Kharagpur Section Student Volunteer Award, 2024.

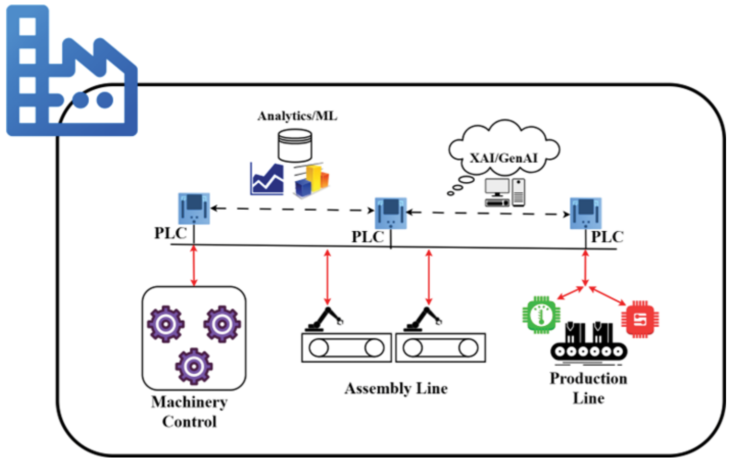


Fig-1: "Connected Manufacturing" - Industrial CPS with embedded AI/ML

To address these challenges, the integration of AI into CPS has become a necessity that paves the way for "intelligent connected manufacturing", with minimum human intervention and near real-time automated decision making, all the while enhancing productivity, quality, and safety [2]. This paradigm shift represents a critical step toward achieving the goals of the next-generation of industrial automation and systems.

Within this emerging landscape, the role of AI-driven automation is not limited to conventional machine learning applications, but extends to advanced methodologies such as Explainable AI (XAI), Generative AI (GenAI), and AI-enabled IoT (AIoT). These technologies empower CPS to autonomously monitor, analyze, and respond to operational conditions, thereby realizing predictive maintenance, intelligent fault detection, and adaptive control. Moreover, distributed learning approaches such as Split Learning (SL) and Federated Learning (FL) allow collaborative training of AI models across industrial subsystems, while ensuring privacy, security, and scalability. Such innovations enable manufacturing systems to evolve from reactive control mechanisms to proactive, intelligent decision-making entities capable of self-optimization in real time.

In this light, the recent emergence of AI-integrated Programmable Logic Controllers (PLCs) has the potential to revolutionize CPS-based industrial control mechanisms [3]. PLCs form a fundamental component of modern industrial processes and systems, which act as the computational and control core of automation systems. PLCs constitute sensors, industrial actuators, monitoring and feedback mechanisms, as well as failsafe mechanisms. Traditionally, PLCs have been designed as monolithic hardware cores that can support only some specific types of end connections over specific protocols. They were not dynamically programmable or scalable with respect to heterogeneous CPS entities [4]. Modern PLCs are being reimagined as intelligent industrial computing cores by embedding AI capabilities directly into the PLCs and virtualizing their functionalities as software-defined modules deployable on containers or cloud infrastructures [5]. This allows industries to achieve significant improvement in process control and management with predictive analytics, maintenance and automated smart decision making. These advancements lay the foundation for next-generation intelligent connected manufacturing, where CPS not only executes control tasks, but also continuously learns, adapts, and collaborates across machines and networks. Factories are now envisaged to become self-reliant and self-sustaining in the light of dynamically changing external factors with minimal or zero human intervention [6].

State-of-the-Art

Cutting-edge research in AI-enabled CPS makes use of sophisticated methods for safe and intelligent industrial automation. While GenAI platforms such as ChatGPT [7] and Gemini [8] allow natural language interaction with industrial systems, XAI improves transparency and trust in CPS decision-making [9]. According to surveys such as Singh and Gill on Edge AI [10], AIoT combines IoT connectivity with AI for distributed edge intelligence [11]. SL [12] and FL [13] offer distributed model training without sharing raw data in order to address scalability and privacy. Modular, cloud-ready, and AI-driven industrial control is made possible by the emergence of AI-integrated PLCs at the system level through Soft-PLCs [14], OpenPLC as an open-source substitute [15], and container-based PLC virtualization [5].

Enabling CPS with AI: The Next-Gen Smart Industrial Solutions

AI has penetrated the present day societies and industries. Through known or unknown means, AI is influencing our everyday lives in an unprecedented manner. Ever since the launch and subsequent boom of Generative AI-based chatbots such as OpenAI's ChatGPT, Google's Gemini, Microsoft's Copilot, and X's Grok AI, we are witnessing the utilization of AI-based results across a wide spectrum of scenarios, from creative art, computer programming, situation analysis to threat detection. With respect to AI-enabled CPS, we can look into the following exciting sub-fields of AI research:

- ***Explainable AI (XAI)***
  Explainable AI (XAI) refers to a specific AI framework that provides output that is readily understood by humans, as they can "explain" the situation to human users and the reason behind the output it has produced. It takes in a particular situation or process as input and produces the actions required to be taken as output, clearly explaining the rationale behind such an actionable output in a readable manner. XAI trains on situations and data in such a manner that it tries to understand the underlying philosophies and principles guiding the situation and produces output in an explainable format. In the context of Cyber-Physical Systems (CPS), XAI plays a vital role by enabling operators and engineers to understand why a system takes a particular action or generates a specific output. This induces a transparency and reliability in AI-enabled decision-making, which deviates significantly from "black-box" based AI-decisions, which are based only on some input without providing any underlying rationale or explanation. By providing insights into model behavior, highlighting key features influencing predictions, and offering human-readable explanations, XAI fosters trust and accountability in AI-driven CPS. XAI enhances debugging and industrial optimized output actions which integrate not only heterogeneous CPS behavior but also incorporate their various state changes, reasonings and performative actions as well, at par with industrial standards.
- ***Generative AI (GenAI)***
  GenAI is perhaps the most disruptive technology to revolutionize the modern computing sphere. Through various GenAI platforms such as OpenAI's ChatGPT [7], X Corporation's Grok AI [16], Meta's Llama [17], Google's Gemini [8], Perplexity [18], GenAI enables the "generation" of new contents such as articles, images, and text based on some input and a trained model on relevant data. With respect to CPS, GenAI provides a framework for AI-enabled User Interface (UI) design whereby industrial managers and technicians are provided with simplified UIs to their on-site PLCs and other monitoring devices, such that they may ask for any queries or data using natural language prompts. The GenAI model can successively respond in similar natural language-based generated texts along with appropriate graphics for fast processing and information analysis, which leads to a significant reduction in analysis time by human agents, lesser stress, and improved productivity.
- ***Artificial Intelligence of Things (AIoT)***
  AIoT amalgamates AI with the IoT technology [11]. It must be noted that industrial CPS are inherently synonymous with IoT, especially Industrial IoT (IIoT) based technologies. The latter provides the relevant networking, sensing, actuation, data processing, and analytics backbone of any CPS. Therefore, unifying IoT with AI by default leads to the development of AI-based CPS as well. While IoT provides pervasive connectivity through a network of sensors, actuators, and devices, AI empowers these connected elements with the ability to analyze data, learn patterns, and make autonomous decisions in real time. Of special interest is the utility of AI in achieving distributed intelligence across the edge [10], which empowers IoT-based industrial nodes such as sensors and actuators to have on-board AI engines that can analyze data in situ and take real-time decisions. While XAI and GenAI, as mentioned above, are specific AI techniques, AIoT can be considered as the enabling technology towards achieving a truly intelligent CPS ecosystem in modern factories.
- ***Split Learning (SL) and Federated Learning (FL)***
  Shifting from generic AI methodologies, we also focus on specific niche areas of Machine Learning (ML), which are the actual under-the-hood engines of AI systems. We are especially interested in the concepts of SL and FL. Traditional ML algorithms employ models such as deep neural networks on a single processing device to be trained with relevant input data. However, with the increase in data set, complexity and variability of the data as well as increased information content, training a neural

network on a single device becomes challenging with an increased number of neurons, hidden layers, and training parameters and latency [19]. Therefore, of late, SL has been proposed, whereby a single large neural network is divided into segments, with each segment containing a part of the overall neural network and executed over a single device, with multiple such segments executing over different hardware cores. A communication channel exists between the segments and the cores over which they execute forward and backward propagation algorithms to train the full network. SL essentially splits a neural net into dependent segments or sub-networks, with each sub-net being executed over its own device/cores, which allows the realization of a single large ML network over distributed nodes that lessens the burden on each node.

On the other hand, considering data privacy issues, there is a consistent requirement that local data gathered by sensors cannot be sent in raw form to a remote cloud over which they may be trained. This issue is particularly relevant for industrial scenarios, as raw sensor data from critical zones should not be transferred over unsafe channels from where they may be intercepted. It is here that FL comes in useful, where sensor data that is gathered is stored locally on the device, and a lightweight ML model trains on the said data. A group of such locally trained models are then sent to a central aggregator, which performs a global aggregation of the models to reach a universally trained model that can then be used for predictions and monitoring. FL forms an extremely important tool for enabling next-generation smart CPS, whereby data gathered from the local edge CPS nodes is trained in situ and the industrial controller can be used to aggregate the local models to obtain a global view, without the loss of data privacy or the fear of data breach in transit.

Fig-2 displays the modular design for an intelligence enabled "thinking industry" whereby the backbone CPS network is assisted by relevant ML/AI verticals, each of which provide their relevant aspects of learning and cognitive abilities.

- ***Applications of Smart Programmable PLCs***
  We now come to a specific application of AI-enabled CPS for the Next-Generation industry, through the design, development and implementation of smart programmable PLCs. As has been mentioned in Section I, PLCs form the computational core and brain of industrial sensing, monitoring and actuation systems, which integrate in real-time with industrial components. The current shift from traditional monolithic PLCs to proprietary hardware to software-based PLCs has opened up a new frontier for easy AI integration through principles of modular design and architecture. This overall concept of Soft-PLC realizes PLC functionalities on general-purpose hardware as fully software modules with integration with XAI, GenAI, and modern learning principles [18]. In this light, the following design principles of smart PLCs are worth investigating.

  ◦ **Virtual PLC**
    As their name suggests, virtual PLCs are a special type of PLCs whereby all the PLC functionalities are executed as virtual functions over general-purpose processing hardware. Their design principles centre on virtualization, modularity, interoperability, and cloud/edge integration, allowing them to seamlessly integrate into connected manufacturing ecosystems. For example, *CodeSys [20], TwinCat [21], and OpenPLC [15]* are some of the popular software implementations of hardware PLCs where suitable virtualized modules can be integrated, allowing direct injection of AI methods within the PLC core.

  ◦ **Cloud PLC**
    Cloud PLCs extend the functionality of traditional PLCs by virtualizing the

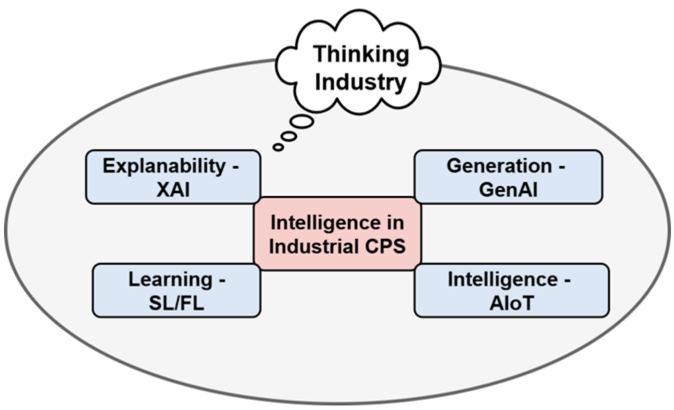


Fig-2: A "Thinking Industry" - AI modules for Industrial CPS relevant modules and deploying them over a remote cloud platform rather than being deployed over local hardware devices. The main difference from the virtual PLCs lies in the fact that the soft PLC codes are deployed over the cloud through suitable PaaS/IaaS enablers, whereas generic virtual PLCs have their modules over local but general-purpose hardware. This shift enables unprecedented scalability, flexibility, and remote accessibility for industrial control systems. Cloud PLCs can integrate seamlessly with advanced AI/ML pipelines, predictive analytics, and digital twins, enabling smarter and more adaptive control strategies. A major concern of Cloud PLCs lies in maintaining seamless connectivity between the remote cloud and the edge CPS devices in a manner that does not disturb the real-time processing and performance of the systems.

- **Containerization in PLC** Extending the concept of virtual PLCs, containerization in PLCs refers to a particular implementation mechanism, whereby the virtual PLC modules are realized as independent and self-sufficient containers over a virtual execution platform [5], instead of being realized as open functions. This simplifies the virtual PLC design procedures as specific local containers with unique execution environments are deployed for PLC-specific tasks, with suitable interfacing between the containers for seamless data transfer. In such an architecture, the relevant AI/ML modules can themselves be realized as self-sufficient containers with unique features that do not directly integrate with core PLC logic but achieve intelligence through safe interfacing between containers. Ease of debugging and modularity in design are the most suitable benefits of having containerized PLCs.

Overall, the various implementations of *SoftPLC* realize intelligent, adaptive, and collaborative computing cores for next-generation industrial CPS. By embedding advanced AI capabilities and leveraging distributed learning paradigms, these virtual PLCs not only execute deterministic control tasks but also evolve into proactive decision-making units that can optimize, explain, and autonomously adapt in real time, towards achieving "connected manufacturing" in a true sense.

SoftPLC Development Principle

The Smart Wireless Applications and Networking (SWAN) Laboratory in IIT Kharagpur [22] have recently taken up the challenges of designing an efficient AI-enabled virtual PLC for fast industrial adoption and based on real-time requirements.

Fig-3 displays the laboratory scale twin PLC training kit available in SWAN Lab that contains traditional hardware PLCs for

Fig-3: Smart PLC Training Kit at SWAN Lab - Automated CPS

their analysis, a human-machine interface (HMI) for interacting with the PLCs. This PLC training kit enables study, analysis and experimentation with hardware PLCs for better understanding and protocol extraction, using which suitable software modules can be developed for virtual PLCs.

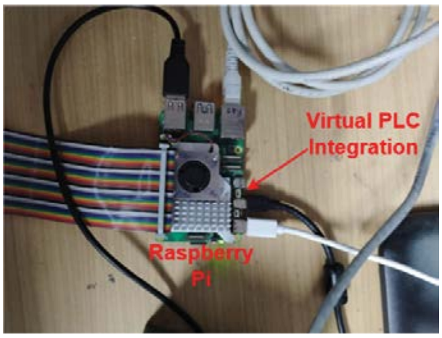


Fig-4: Realizing VirtualPLC over Raspberry Pi - Generic Computer

Fig-4 displays the development of such a virtual PLC over a Raspberry Pi which acts as the general purpose computing hardware and execution platform. As shown in Fig-4, the virtual PLC cores can be modified through software as per requirement, with which suitable AI/XAI modules can be integrated that can provide real-time explainable feedback-cum-decision for real-time industrial CPS inputs. Additionally, SL/FL are being implemented over a distributed set of such virtual CPs for collective edge learning, whereas GenAI integration with the human-machine interface (Fig-3) can provide natural language prompt-based interfacing for both input and output data.

Conclusion

As we herald the age of AI, the future CPS and industrial automation must also integrate AI heavily in all its aspects. Armed with exciting concepts such as XAI, GenAI and AIoT along with its suitable sister and enabling technologies such as Split and Federated Learning, the Next-Generation industries will see a revolution of connected components, where AI agents can gather data, perform analytics operations, understand the situation and its threat in human terms and act accordingly in real-time for most efficient situation mitigation with minimal or no human intervention. This "situational awareness" of CPS architecture through AI will indeed make an industry a "living" entity with its own brain and heart. As a specific application, PLCs are already being softwarized for convenient AI integration, and we hope to usher in a new generation of "connected manufacturing" in its true.

References

1. H. Xu, W. Yu, D. Griffith, and N. Golmie, "A survey on Industrial Internet of Things: A Cyber-Physical Systems perspective," IEEE Access, vol. 6, pp. 78 238–78 259, 2018.
2. T. Yang, X. Yi, S. Lu, K. H. Johansson, and T. Chai, "Intelligent manufacturing for the process industry driven by industrial artificial intelligence," Engineering, vol. 7, no. 9, pp. 1224–1230, 2021.
3. N. Dhameliya, "Revolutionizing PLC systems with AI: A new era of industrial automation," American Digits: Journal of Computing and Digital Technologies, vol. 1, no. 1, pp. 33–48, 2023.
4. M. K. Babu and Y. Suthari, "Secure and intelligent PLC systems: Integrating artificial intelligence for enhanced industrial control and data privacy," Computer Fraud and Security, vol. 11, pp. 21–29, 2023.
5. R. Queiroz, T. Cruz, J. Mendes, P. Sousa, and P. Sim~oes, "Container-based virtualization for real-time industrial systems—a systematic review," ACM Computing Surveys, vol. 56, no. 3, pp. 1–38, 2023.
6. N. Almtireen, V. Reddy, M. Sutton, A. Nedvidek, C. Karn, M. Ryalat, H. El-Moaqet, and N. Rawashdeh, "PLC-controlled intelligent conveyor system with AI-enhanced vision for efficient waste sorting," Applied Sciences, vol. 15, no. 3, p.1550, 2025.
7. T. Wu, S. He, J. Liu, S. Sun, K. Liu, Q.-L. Han, and Y. Tang, "A brief overview of ChatGPT: The history, status quo, and potential future development," IEEE/CAA Journal of Automatica Sinica, vol. 10, no. 5, pp. 1122–1136, 2023.
8. G. Team, R. Anil, S. Borgeaud, J.-B. Alayrac, J. Yu, R. Soricut, J. Schalkwyk, A. M. Dai, A. Hauth, K. Millican et al., "Gemini: a family of highly capable multimodal models," arXiv preprint arXiv:2312.11805, 2023.
9. M. Mersha, K. Lam, J. Wood, A. K. Alshami, and J. Kalita, "Explainable artificial intelligence: A survey of needs, techniques, applications, and future direction," Neurocomputing, vol. 599, p. 128111, 2024.
10. R. Singh and S. S. Gill, "Edge AI: a survey," Internet of Things and Cyber-Physical Systems, vol. 3, pp. 71–92, 2023.
11. S. I. Siam, H. Ahn, L. Liu, S. Alam, H. Shen, Z. Cao, N. Shroff, B. Krishnamachari, M. Srivastava, and M. Zhang, "Artificial Intelligence of Things: A survey," ACM Transactions on Sensor Networks, vol. 21, no. 1, pp. 1–75, 2025.
12. P. Vepakomma, O. Gupta, T. Swedish, and R. Raskar, "Split learning for health: Distributed deep learning without sharing raw patient data," arXiv preprint arXiv:1812.00564, 2018.
13. Q. Yang, Y. Liu, T. Chen, and Y. Tong, "Federated machine learning: Concept and applications," ACM Transactions on Intelligent Systems and Technology (TIST), vol. 10, no. 2, pp. 1–19, 2019.
14. Q. Liang and L. Li, "The study of soft PLC running system," Procedia Engineering, Vol. 15, pp. 1234–1238, 2011.
15. T. R. Alves, M. Buratto, F. M. De Souza, and T. V. Rodrigues, "OpenPLC: An open source alternative to automation," in IEEE Global Humanitarian Technology Conference (GHTC 2014). IEEE, 2014, pp. 585–589.
16. Grok — xAI — x.ai," https://x.ai/grok, [Accessed 18-09-2025].
17. H. Touvron, T. Lavril, G. Izacard, X. Martinet, M.-A. Lachaux, T. Lacroix, B. Rozi`ere, N. Goyal, E. Hambro, F. Azhar et al., "Llama: Open and efficient foundation language models," arXiv preprint arXiv:2302.13971, 2023.
18. Perplexity — perplexity.ai," https://www.perplexity.ai/, [Accessed 18-09-2025].
19. K. Pfeiffer, M. Rapp, R. Khalili, and J. Henkel, "Federated learning for computationally constrained heterogeneous devices: A survey," ACM Computing Surveys, vol. 55, no. 14s, pp. 1–27, 2023.
20. https://www.codesys.com/, [Accessed 19-09-2025]
21. V. G. Beckhoff Automation GmbH Co. KG, H¨ulshorstweg 20, "TwinCAT — Automation software — beckhoff.com," https://www.beckhoff.com/en-en/products/automation/twincat/, [Accessed 18-09-2025].
22. SWAN — cse.iitkgp.ac.in," https://cse.iitkgp.ac.in/~smisra/swan/, [Accessed 18-09-2025].

Artificial Intelligence Deployment in Metallurgical Industries

Dr. Satyam S. Sahay, FNAE, Head - Advanced Engineering & John Deere Fellow, Enterprise Tech & Engineering Center, India & Mexico, Pune

Abstract

During the last decade, AI has become an imperative for any successful business, including metallurgical industries such as primary metal producers (steel, aluminum), the Tier 1 or 2 suppliers of OEMs (foundry, forging, machining, heat treating). The present article outlines some of the specific AI applications in these metallurgical industries. The primary metal producers are characterized by high material processing, energy intensive processes with end products of limited shape and size complexity. The AI/ML deployments in primary metal producers accelerate the discovery of new alloys, optimizes and controls the unit operations for operational efficiency, energy reduction, first pass yield and quality. Furthermore, AI leverage for scheduling, material flow and preventive maintenance have created significant value. In the case of OEMs, the design and process complexities of the individual parts are very high, making supply chain, logistics, material flow, inventory control very important. In addition to these critical functions, AI is also leveraged for rational choices among material-process-sourcing, process monitoring and asset management. The availability of data across the process chain provides significant opportunity to develop AI/ML models for primary metal producers as well as OEMs. The present article also describes the increasing applications of AI in additive manufacturing, including, design, material discovery, process optimization, control and property predictions. Finally, the near-term applications of GenAI in streamlining the multimodal materials information for materials engineering groups along with influencing the adjacent functions such as design, manufacturing, quality and supply chain have been discussed. This article is an excerpt from few chapters of upcoming ASM Handbook on AI/ML Applications in Materials Engineering (Vol 26).

Dr. Satyam S. Sahay

Dr. Satyam Sahay, FNAE, is a John Deere Fellow and Head of Advanced Engineering & Manufacturing Technologies at John Deere Enterprise Technology & Engineering Center - India, Mexico and Brazil. As a John Deere Fellow, he leads Advanced Materials Engineering, with focus on Product Circularity and analytics, modeling and Integrated Computational Materials Engineering (ICME). During the last decade, he has applied analytics and AI/ML to diverse John Deere functions ranging from marketing, product engineering, manufacturing, supply chain and customer support with significant business impact. He is a Visiting Professor of Practice at Department of Sustainable Energy & Engineering at IIT Kanpur.

Dr. Sahay has graduated from BIT Sindri (Metallurgical Engineering - 1986-90), MTech from IIT Kanpur (1992) and PhD from University of Utah (1995). He has worked for 12 years at Tata Research Development and Design Center before joining John Deere Technology Center Pune (2008). He is Fellow of ASM International (2013) and Fellow of Indian Institute of Metals (2011). He is recipient of Young Metallurgist of Year (2004), Metallurgist of the Year (2008) and Tata Group Promising Innovation Award (2008). He has 9 Patents, 6 Trade-secrets, 75+ Journal Papers, 100+ Conferences, 1500+ Citations. He provides professional leadership through contributions in professional society (IIM & ASM) committees, serves on five international journal boards and ASM Handbook Committee, and has co-chaired several major conferences.

Introduction

Artificial Intelligence (AI)-based solutions have been leveraged in materials engineering applications for several decades. The initial efforts included defect classification for NDT tests (Ref 1), predicting impact toughness of welded joints (Ref 2) to error estimation for control systems in steel mills (Ref 3). Most of these early applications of AI in the metallurgical industry had roots in academia or proprietary control solutions from automation service providers. During the last decade, Artificial Intelligence and Machine Learning (AI/ML) have been democratized due to (i) the adoption of the fourth industrial revolution (Industry 4.0) (Ref 4) and the resultant digitalization, with data becoming available across the processes and business value chain, (ii) more affordable on-premise as well as on-cloud compute capabilities, (iii) accelerated democratization of AI/ML through digital upskilling and the availability of low-code and no-code tools, and (iv) a growing pool of recent graduates across engineering disciplines equipped with AI/ML skills (Ref 5). This has resulted in rapid digital dexterity across industries, enabling low-cost experimentations. However, even with widespread adoption of AI methods, a recent 2025 study by MIT has reported (Ref 6) that out of $30-$40B enterprise investments on GenAI adoption, 95% of organizations experienced zero business impact (Ref 6). The core barriers were not found to be infrastructure, regulation or talent but contextual adaptation and the ability to improve model performance over time.

AI Applications in Metallurgical Sectors

Metallurgical sectors span a very diverse range of industries, from primary metal producers to original equipment manufacturers (OEM) for automotive, agriculture machinery, construction and mining equipment, aerospace, and home-appliances manufacturing. Additionally, tier one and tier two suppliers, such as foundries, machining, heat treating, metal forming, and forging, support the OEMs. Each of these manufacturers operates in a distinct context with varying complexities.

Primary metal producers, such as integrated steel plant, primary aluminum, copper or zinc producers are essentially process industries, with large raw material processing capabilities. They produce liquid metal and subsequently form it into standard solid products, such as bars, rods, plates and sheets. For example, integrated steel plants produce steel of standard grades, defined by chemical composition, and thermomechanical processing (hot-rolling, annealing, cold rolling) to achieve the specified mechanical properties. The design complexities (in terms of shape and forms) for the primary metal producers are relatively low, allowing a focus on high-volume production lines (Fig-1). The scope of AI/ML deployments in such organizations includes the discovery of new alloys, process optimization and control of unit operations with an objective of cost reduction, energy reduction, first pass yield and productivity enhancement (Ref 7-9). Furthermore, scheduling processes and material flow in this sector become very important for the process and cost optimization. AI has also been extensively leveraged for asset management and preventive maintenance among the primary metal producers.

OEMs have undergone significant digital transformation during the last decade with their connected and intelligent product offerings for their customers. These product offerings have also helped them develop and mature their in-house AI capabilities, with an impact on internal business processes and manufacturing operations. OEM products (e.g. automotive, agriculture and construction equipment, aerospace, computers, mobiles and home appliances) comprise tens of thousands of individual components, sourced from tier one and two suppliers across the globe and assembled in their factories. The design and process complexities of these individual parts are significant, leveraging diverse operations (e.g. forging, casting, machining, welding). Some of the AI applications in the OEM include logistics, material flow and inventory control, cost prediction of individual parts, rational choices among material-process-sourcing, process monitoring, asset management and preventive maintenance. In addition, in OEM, AI also gets leveraged for design optimization (e.g. casting), process

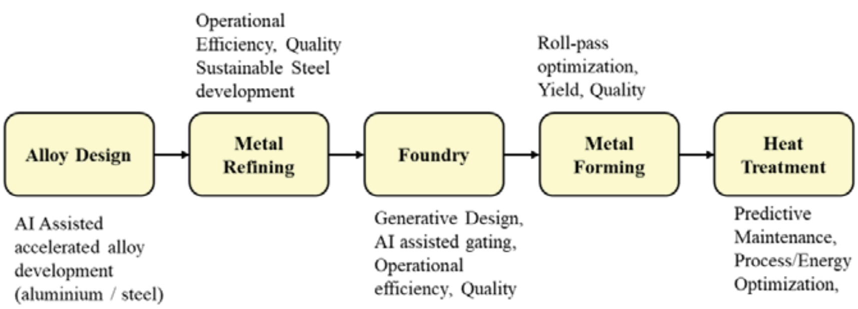


Fig-1: Examples of AI leverage in metallurgical industries optimization (e.g. casting, machining, heat treating), material optimization (e.g. material choices, steel grade selection) and managing defects and quality (e.g. casting defects, welding distortion, failures in shaft and structures).

- ***AI Applications for Insights Across Process Chain***

Although first principle mathematical models have been leveraged in metallurgical unit processes for decades, through-process models across unit processes are very challenging due to dependence on multiple upstream unit processes. The availability of data across the process chain provides significant opportunity to develop AI/ML models for the entire process chain. This is illustrated, along with limitations, in the following example of deep drawing grade steel.

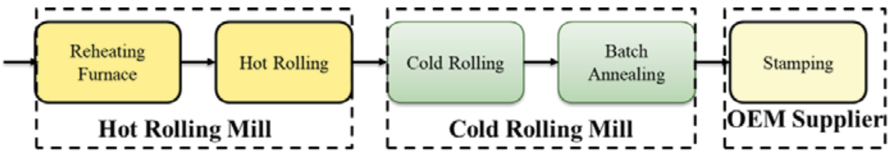


Fig-2: Interconnected process chain for deep drawing steel

The process chain for producing deep drawing steel suitable for automotive panels is given in Fig-2. These process steps are carried out in two or three different organizations. Reheating and hot rolling operations are carried in a hot-strip mill, whereas cold-rolling and annealing operations are carried out in a cold-rolling mill. These two unit-operations may be part of the same integrated steel plant or there can be stand-alone cold rolling mill, which procures hot rolled coils from other organizations. Deep drawing operations are invariably carried out at the automotive tier one or tier two suppliers, which are not part of the steel plant. Deep drawing characteristics at the end of the process chain strongly depend on all the process steps illustrated in this figure. For example, in case of Aluminum-Killed (AlK) deep drawing grade steel, reheating temperatures are intentionally kept high to retain AlN precipitates in solid solution. Furthermore, to prevent premature precipitation of AlN in hot rolling mill, coiling temperature at the end of the hot-strip mill are kept low. Precise control of these process temperatures promotes AlN precipitation during the very slow heating phase of batch annealing process. The precipitation of AlN at the sub-grain boundaries during the batch annealing process retards the recrystallization and promotes preferred {111} texture, with high deep drawing characteristics (Ref 10).

Requirements and context significantly change for different material grades (steel grade changing from AlK to interstitial-free (IF) steel) or different process (annealing changing from batch annealing to continuous annealing). These subtle process interactions are insights from several decades of engineering research of physical metallurgy and are leveraged for designing these process steps (Ref 10). However, these insights are primarily empirical in nature, without a comprehensive first principle based through-process model. AI/ML approaches provide an opportunity to create such a model based on the process, material and operational data. For example, from a stable upstream process (known material sources and consistent process), material certificates can be used to predict the stamping quality using AI/ML models.

There are several such examples of inter-dependent metallurgical processes and their impact on the final product quality. AI/ML-based approaches make such highly complex process chain modeling tractable due to the availability of significant volume of material and process data. These models can be leveraged for process optimization resulting in productivity enhancement, energy reduction and defect reduction.

- ***AI Application in Additive Manufacturing***

Additive manufacturing is a disruption at the intersection of materials, design, manufacturing, and supply-chain, where a 3D part or an assembly can be created through layer-by-layer deposition of the powders (Ref 11). Additive manufacturing provides unique manufacturing advantages, such as (a) the ability to create parts without any upfront tooling costs, which provides business opportunities for rapid prototyping and production of spare parts for old machines or low volume production parts, (b) the ability to create high performance parts with complex designs, which is not possible in traditional manufacturing processes, (c) the ability to precisely repair a damaged part, a capability extensively used in aerospace engine repair and maintenance.

AI/ML methods have been increasingly finding utility in additive manufacturing, including generative design, material discovery, manufacturing process optimization, in situ process control, and property predictions. Some of these applications have been outlined below (Ref 12-15).

- **Additive Design:** The unconstrained design possibilities from additive manufacturing can be leveraged by optimizing designs through AI tool-sets. For example, deep neural network ML methods have been used for quick design iterations and efficient topology optimization (Ref 16), whereas CNNs have been leveraged for training the intermediate topologies rendering design process 20x more efficient (Ref 16). In addition, Generative design tools leverage ML algorithms to generate and optimize vast design space possibilities, meeting the performance requirements from the structure (Ref 17).
- **Material Discovery:** The combinatorial possibilities of leveraging material type and their volume fraction, size, and geometry provides significant opportunities for creating phases and microstructures at specific locations as well as creating graded or composite structures. Material discovery also provides unique opportunity for leveraging AI/ML methods in additive manufacturing, including accelerated material development, solving inverse problems of identifying constituents for target material properties. High throughput experiments integrated to machine learning algorithms can be leveraged for accelerated discovery of novel materials.
- **Process Optimization:** Additive Manufacturing process optimization is one of the highest use cases for AI/ML applications. Optimizing process parameters such as layer height, printing speed, laser power, part orientation, temperature, and material type for target properties is very effective through AI/ML models. These models can also be efficiently deployed in the real-time process control. ML methods like K-mean clustering have been used for optimizing the build orientation and direction of the parts. Furthermore, based on the historical datasets, the pre-processing steps as well as post-processing heat treatment can be integrated through AI/ML based models. Such integration of multiple processing steps is more complex and challenging through conventional first principles modeling than AI/ML based modeling approaches. AI/ML based defect prediction and control tools have been used for improving the quality of additive manufactured parts (Ref 13, 15, 16).

Generative AI and Its Near-Term Applications in Materials Engineering

Generative AI (GenAI) gained widespread attention two years ago with the public release of ChatGPT by OpenAI. It attracted over one million users within a short period, making it the fastest growing new application. Since then, there have been several commercially available GenAI tools for natural language processing and conversation, computer vision, and multimodal models combining vision and language (Ref 18, 19). Generative AI has been envisioned to be a transformative technology, which can revolutionize the way materials are discovered or designed (Ref 20), processed or manufactured, and used for engineering realization (Ref 21). Nevertheless, breakthrough applications that have truly revolutionized materials engineering-related industries remain limited. This section envisages four realistic near-term applications of Generative AI.

<u>GenAI Aided streamlining materials information for materials science and engineering groups:</u>

Many materials science and engineering groups, in academia, research, or industry have accumulated knowledge bases of several decades. These knowledge bases are (a) primary data collected from laboratory experiments, validations at pilot or industry scale, and quality test data, (b) contextual, team specific information, such as laboratory notes, internal technical reports, standard operating procedures, analysis reports, quality reports, and trade-secrets, (c) computer codes generated for various transformations, modeling and simulations, and their results in varied forms, (d) scientific literature including standards, journal and conference papers, and patents. Furthermore, this information is multimodal, encompassing microstructure images, X-ray diffraction patterns, videos of in situ examination studies, crystal structure, text data, formatted data obtained from various tests, mechanical property test results in graphical form.

Many materials engineering teams

have envisioned a knowledge management system for their group, and many have collated knowledge within their group in the form of SharePoints, wiki pages, or even hierarchical file structures on their computer systems. However, due to the multimodal nature of these knowledge bases, these attempts are often reduced to static repositories without inference engines or conversational capabilities. Generative AI provides an unprecedented opportunity to create a large language multimodal model from these diverse knowledge bases with possibilities to create outputs in varied formats. Furthermore, this system can evolve over time, not only with updated data but also with improved capabilities and accuracy. This system will also accelerate the engineering workflows, automating analysis protocols and report generation. Many of these ideas are already being realized through contextual large language GenAI models.

GenAI aided Democratization of Computational Materials Engineering:

One of the prominent usage of GenAI in the software sector is accelerating the software development through automated code generation. Computational materials engineering and process modeling simulation development have been very niche skilled jobs. There is shortage of skilled personnel in this space and developing this competency in an organization takes significant effort. A projected near term application of GenAI in materials engineering is the democratization of computational materials engineering. GenAI can accelerate engineering workflows, improve efficiency in model creation and help standardize the codebases. Over time, it can also significantly reduce the time required to incubate this competency for new teams or organizations.

GenAI enabled tools to aid designers for materials selection in Original Equipment Manufacturers (OEM):

In Original Equipment Manufacturer (OEM), several materials engineering related decisions are made by adjacent functions, such as design (materials selection), manufacturing (materials processing recipe), quality (conformance to specifications), and supply chain (alternate materials grade for different geography). For example, designers typically select materials types or grades based on their heuristic knowledge or by copying materials specification from similar parts used in the organization. Many of these selections go wrong and are rectified through issue resolution or continuous improvement processes. It must be noted that the specification of a material grade in an OEM has nuances such as its ability to meet the functional requirements, its manufacturability, its availability in the manufacturing location, low cost, and meeting sustainability considerations. Furthermore, for OEMs having manufacturing facilities in multiple geographies, the equivalent grades in different countries meeting the organizational grade standards becomes cost imperative. In such complex operating environments, designers having their preferences and biases on materials selection and materials processing selections lead to a divergent material palette. GenAI provides an attractive alternative to create materials selection tools – from the existing parts data, internal and external materials standards, and cost data from supply chain. Such a tool will also promote organizational consistency for the materials selection process driven by design engineers.

GenAI enabled expert system for Failure Analysis:

Failure Analysis is a specialized skill and most organizations have only a few experts with this expertise. GenAI provides an opportunity to collate all the historical failure data in varied forms including images, microstructure, test reports, warranty, and service records. Furthermore, all the historical remedial actions can be stitched together along with impact. Subsequently, GenAI tool can create an expert system from this varied dataset, with an ability to diagnose new failures as well as providing their remedial measures from similar parts failure in the past. Such systems were attempted in the past, but mostly with unimodal datasets. GenAI enables a fresh approach using multimodal organizational databases, capturing operating context and their evolution over time to improve accuracy and utility.

Conclusions

There are significant opportunities for leveraging AI/ML in diverse metallurgical industries, ranging from primary metal producers to OEMs and tier one or two suppliers of OEMs. The context of each of these industries is different and therefore requires intentional identification of opportunities. Several specific AI/ML opportunities have been highlighted in this chapter. It is important to judiciously leverage engineering knowledge, and the first principle-based modeling approaches evolved over several decades in conjunction with

AI/ML models. AI/ML models are more efficient for creating surrogate models from first-principle models or directly from operational data of interconnected processes. Such models are effective primarily in the operational regime from which the data has been obtained. They are less effective (necessitating complex formulations), in solving complex non-linear problems or discovery problems (e.g. developing new alloys). Additionally, in the industry context, (i) return-of-investment of AI/ML effort, (ii) alignment to business strategy and functional priorities, (iii) creation of standard solutions integrated in the functional workflow with scaling capability, (iv) strategic development of AI/ML capabilities, and (v) being intentional about responsible AI development while managing risk, become key considerations. It is important to note that AI/ML is an evolving domain with significant business opportunities, and some of these issues will be resolved during its maturity journey.

This article is an excerpt from few chapters of upcoming ASM Handbook on AI/ML Applications in Materials Engineering (Vol 26).

References

1. C H Chen, Applying and validating neural network technology for nondestructive evaluation of materials, *Conference Proceedings., IEEE International Conference on Systems, Man and Cybernetics,* Cambridge, MA, USA, 1989, p 1208-1209.
2. H. K. D. H. Bhadeshia, D. J. C. MacKay and L. E. Svensson, The Impact Toughness of C–Mn Steel Arc–Welds - A Bayesian Neural Network Analysis, *Materials Science and Technology,* Vol 11, 1995, p 1046-1051.
3. M Jansen, E Broese, B Feldkeller, O Gramckow, T Poppe, M Schlang, G Sörgel, Application of Neural Networks to Process Control in Steel Industry, I*FAC Proceedings Volumes,* Vol 31, 1998, p 177-182.
4. A. Mathur, A. Dabas and N. Sharma, "Evolution From Industry 1.0 to Industry 5.0," 2022 *4th International Conference on Advances in Computing, Communication Control and Networking (ICAC3N),* Greater Noida, India, 2022, IEEE, pp. 1390-1394.
5. S. S. Sahay, Industry 4.0 meets Heat Treating, *Advanced Materials and Processes,* Dec. 2016, p 59–61
6. A. Challapally, C Pease, R Raskar, P Chari, MIT Research Report: The GenAI Divide: State of AI in Business 2025, July 2025
7. S. S. Sahay, U. Tewary, G. Mohapatra,, "Applications of Artificial Intelligence and Machine Learning in Metallurgical Industries," *ASM Handbook,* Vol 26 – in press.
8. A. Vahid, S. Rana, S. Gupta, P. Vellanki, S. Venkatesh, T. Dorin, New Bayesian optimization-based design of high-strength 7xxx-series alloys from recycled aluminum, *JOM,* Vol 70, 2018, p 2704–2709.
9. J.-W. Lee, C. Park, B. Do Lee, J. Park, N.H. Goo, K.-S. Sohn, A machine-learning-based alloy design platform that enables both forward and inverse predictions for thermo-mechanically controlled processed (TMCP) steel alloys, *Scientific Reports,* Vol 11, 2021, p 11012.
10. RK Ray, JJ Jonas, RE Hook, Cold Rolling and annealing textures in low carbon and extra low carbon steels, Intl Mater Rev, Vol 39, 1994, 129-172.
11. Additive Manufacturing Design and Applications, Editors: M Seifi, DL Bourell, W Frazier, H Kuhn, Vol 24A, ASM Handbook, 2023.
12. A Panesar, V Carollo, M Jamal, Simulation-driven design and role of optimization in design for additive manufacturing, Vol 24A, Additive Manufacturing Design and Applications, Metals Handbook (2023), 138-158.
13. E Reutzel, J Petrich, DJ Corbin, Application of machine learning to monitor metal powder-bed fusion additive manufacturing processes, Vol 24A, Additive Manufacturing Design and Applications, Metals Handbook (2023) 360-373.
14. A Kitt, Data analytics and machine learning in metal additive manufacturing – challenges, segmentations and applications, Vol 24A, Additive Manufacturing Design and Applications, Metals Handbook (2023), 177-183
15. J Qin, F Hu, Y Liu, P Witherell, CCL Wang, DW Rosen, TW Simpson, Y Lu, Q Tang, Research and application of machine learning for additive manufacturing, Additive Manufacturing, 2022, 52, 102691.
16. C Wang, XP Tan, SB Tor, CS Lim, Machine learning in additive manufacturing: state-of-the-art and perspectives, Additive Manufacturing, 2020, 36, 101538.
17. P Koul, A review of generative design using machine learning for additive manufacturing, Advanced in Mechanical and Materials Engineering, 41, 2024, 145-159.
18. Y Cao, S Li, Y Liu, Z Yan, Y Dai, P Yu, L Sun, A Survey of AI-Generated Content, ACM Computing Surveys, 2024, https://doi.org/10.1145/3704262
19. ZB Akhtar, Unveiling the evolution of generative AI: a comprehensive and investigative analysis towards LLM Models (2021-2024) and beyond, J of Electrical Systems and Information Technology, 2024, 11, 22.
20. Y Liu, Z Yang, Z Yu, Z Liu, D Liu, H Lin, M Li, S Ma, M Avdeev, S Shi, Generative artificial intelligence and its applications in materials science: Current situation and future perspectives, Journal of Materiomics 9 (2023) 798-816
21. AS Fuhr, BG Sumpter, Deep Generative Models for Materials Discovery and Machine Learning, Accelerated Innovation. Front. Mater, 2022, 9, 865270

Industrial Cyber-Physical Systems over Wireless

Prof. Anurag Kumar, FNAE, INSA Distinguished Professor, Department of Electrical Communication Engineering and former Director, Indian Institute of Science, Bengaluru

Arpan Chattopadhyay, EE Department, Indian Institute of Technology, New Delhi

Introduction

- ***Cyber-Physical Systems***

The term Cyber-Physical Systems (CPS) was coined in a US National Science Foundation white-paper by Baheti and Gill in 2011 [7]. Any CPS is concerned with controlling and optimising the performance of a technical system associated with a physical domain. Examples would be a moisture and nutrition control system for a farm, a water quality control system for a city, or the structural safety monitoring system for building or a bridge.

Fig-1 depicts a layered view of Cyber-Physical Systems. Evidently, each CPS system design would depend crucially on the physical aspects of the domain, which is why this aspect forms the lower-most layer. Embedded in the domain would be sensors and actuators; for example, soil moisture and nitrogen sensors, and associated systems for watering and applying nitrogen supplements. Since the domain could be remote (as in a farm), or the sensors and actuators could be mobile (for example, drones as sensors and actuators), a communication network (often based on wireless technology) would connect the top-most layer of the CPS hierarchy to the sensors and actuators. Finally, the top layer of a CPS comprises the computing and the algorithms for making inferences about the physical domain (*"Is there a pest infestation in the farm? Which pest? Where?"*), making decisions (e.g., a 100 sq m. area to the North-East of the farm has an infestation that needs to be treated by a particular pesticide), and taking actions by, for example, sending some drones carrying pesticide to be sprayed, in a focused manner, over the area of incipient infestation.

Although named as such for the first time in [7], CPSs have existed since microprocessors and microcontrollers began to be embedded into industrial control systems, soon after their advent in the 1970s. For example, the Bosch

Prof. Anurag Kumar

Prof. Anurag Kumar, FNAE, (B.Tech (1977) IIT Kanpur, PhD (1981) Cornell Univ.) was a Member of Technical Staff in AT&T Bell Laboratories (1981–1988), before returning to India and joining the Indian Institute of Science (IISc) as a faculty member in the ECE Department. He became a Professor in 1996, the Director of IISc during 2014–2020, and an Honorary Professor after his superannuation in 2020. Since 1st January, 2024, he has been an Indian National Science Academy (INSA) Distinguished Professor.

He has published about 200 peer-reviewed papers in journals and conferences, in the area of performance analysis, optimisation, and control of communications networks and distributed systems. He was the 1977 President's Gold Medallist in IIT Kanpur.

He has been elected Fellow of the IEEE, the Indian National Science Academy (INSA), the Indian National Academy of Engineering (INAE), the Indian Academy of Sciences (IASc), and The World Academy of Sciences (TWAS). He received the 2015 Vasvik Award for Information Technology, and the 2017 IEI-IEEE Award for Engineering Excellence.

He is a recipient of the J.C. Bose National Fellowship, awarded by the Department of Science and Technology, for the period 2011–2021.

fuel injection system had already incorporated microprocessor based control in 1979 [1]. Such systems could be called *monolithic* Cyber-Physical Systems, since the sensing, communication, and control were tightly coupled by dedicated communication links inside the fuel-injection system. Fig-1, on the other hand, has a larger vision, as it includes the concept of a *networked* CPS, in which the components, the domain, with embedded sensors and actuators, and the inference and control could be separated by a communication network, wired or wireless. Indeed, the entity being controlled could itself be in many locations for example surveillance drones, with the inference and control being distributed as well.

Quoting from the Baheti and Gill white-paper, "The ability to interact with, and expand the capabilities of, the physical world through computation, communication, and control is a key enabler for future technology developments". Indeed, the convergence of computing, communication, and control is one of the key aspects of modern Cyber-Physical Systems, and is also the aspect that has driven some of the research efforts of the authors of this article.

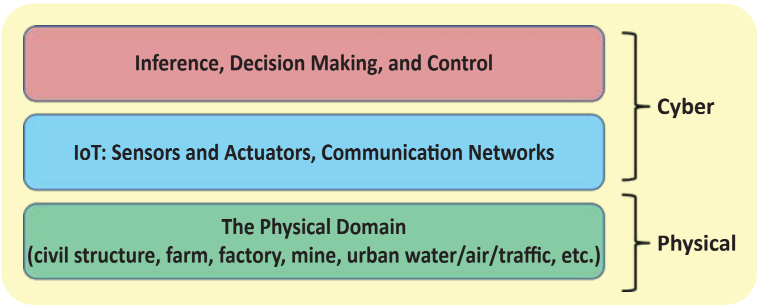


Fig-1: The layers in a Cyber-Physical Sytem

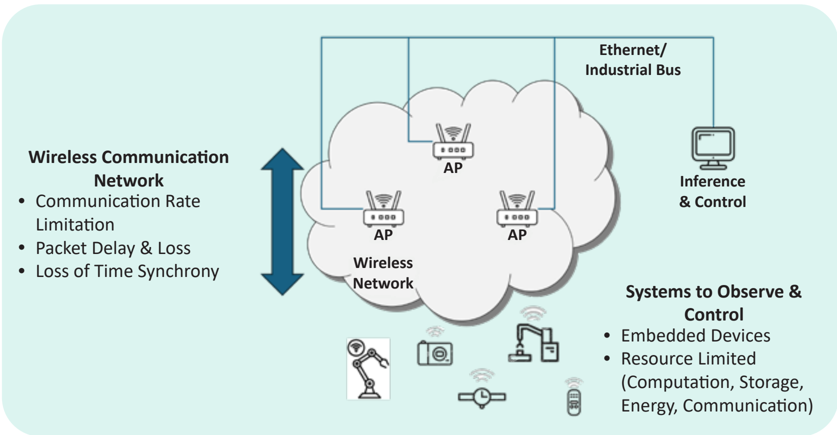


Fig-2: Control over wireless in an Industrial Cyber-Physical System

- ***Industrial CPS over Wireless Networks***

Industrial Cyber-Physical Systems for Industry 4.0 will comprise fixed machines, robots, guided vehicles, drones, etc., all internetworked with edge-computing. The communication fabric of these systems would necessarily be wireless networks, to enable mobility. Even for condition monitoring of fixed machine, where machine mounted sensors are connected to the edge-computing, wireless connectivity would be favoured, to avoid the engineering, deployment, and maintenance costs of electrical or optical cables. Further, retrofitting of existing legacy factories with modern Industry 4.0 applications, would be more easily achieved with wireless communication between the components. For high speed indoor wireless connectivity, the dominant technologies today are Wi-Fi (as standardised in the IEEE 802.11 series of standards) and 5G-NR (as standardised by 3GPP (Third Generation Partnership Project)).

Wi-Fi, originally, a technology for indoor wireless access to the Internet (indeed, called the "Wireless Ethernet" at that time) has evolved from 2 Mbps PHY bit rates[1] to Wi-Fi 7 (IEEE 802.11be) which can offer PHY bit rates in

Prof. Arpan Chattopadhyay

Prof. Arpan Chattopadhyay obtained his B.E. degree in Electronics and Telecommunication Engineering from Jadavpur University in 2008, and his M.E. and Ph.D. degrees in Electrical Communication Engineering from the Indian Institute of Science, Bangalore, in 2010 and 2015, respectively. He is currently an Assistant Professor in the Department of Electrical Engineering at the Indian Institute of Technology Delhi. Previously, he held postdoctoral positions at INRIA, Paris, and the University of Southern California, Los Angeles. His research interests include communication, signal processing, and online learning. He currently serves as an Associate Editor for IEEE Signal Processing Letters and IEEE Transactions on Aerospace and Electronic Systems.

excess of 23 Gbps. Air-time access in Wi-Fi is, however, based on random access and there are no mechanisms for global network coordination, which leads to Wi-Fi network not being able to guarantee bulk transfer throughputs, nor latency bounds. Several techniques have been introduced in IEEE 802.11ax (High Efficiency WLAN (Wireless Local Area Networks)), such as Spatial Reuse where the aim is to dynamically manage the transmission power and the carrier sense threshold when there are overlapping cochannel BSSs[2]. Another feature called Target Wake Time (TWT) has been introduced, where an AP (Access Point) negotiates sleep-wake schedules with an associated STA (Station) or group of STAs such that these STAs are active only in their respective wake periods and sleep otherwise, thus reducing contention. However, these features cannot be properly utilized to achieve globally optimal network performance, without coordination among the APs.

On the other hand 5G-NR has evolved from cellular technology, can provide PHY rates of up to 10 Gbps, over 100s of meters outdoors, is centrally managed, and can provide finegrained QoS (Quality of Service) to flows. Although designed for cellular networks, with the requirements of Industry 4.0 in mind, there is increasing impetus towards deployment of 5G-NR networks for such industrial control applications requiring high throughputs and tight latency bounds.

There is widespread deployment of Wi-Fi networks in campuses, enterprises, and even factories, and there is rapid emergence of 5G-NR private networking solutions. Given, however, the aggressive cost-points of Wi-Fi technology, and the complexity of even the simplest 5G-NR deployments, it is important to explore a **converged** wireless interconnection network comprising Wi-Fi and 5G-NR subnetworks, disjoint or overlapping. Each technology should have controls that can provide certain types of QoS. For example, ADWISER technology [40], developed in the ECE Department, IISc, can provide globally optimal TCP[3] throughputs across multiple APs, while prioritising downlink real-time flows, such as video. On the other hand 5G-NR, with proper scheduling, can be configured for a variety of QoS profiles. Thus, in a factory setting, for some applications, the less expensive and ubiquitous Wi-Fi, enhanced with ADWISER would suffice, whereas for applications requiring tight latency bounds 5G-NR would be required. In situations where a certain QoS profile is available across both technology, the converged Wi-Fi 5G-NR network should support QoS-handovers either way.

A major technical problem encountered, when the controller (running in the edge-computer) communicates with the controlled system over a wireless network (Fig-2), is that the measurements and the controlled commands encounter the deficiencies of the wireless network, as shown in Fig-2. The wireless network can be designed and dynamically controlled in a way that the deficiencies (such as latency) are within limits. Yet, it is now well-known that such a situation requires new considerations to be brought into the design of the controller, to account for the limitations of the wireless communication network [36], [31], [37].

- ***State of the Art***

Industry 4.0 is characterised by multirobot systems, edge analytics, and a variety of information and communication technologies [10]. These technologies are expected to assist in condition monitoring, networked control, online optimisation, and the development of digital twins. These applications come with different levels of requirements for the supporting wireless network, in terms of reliability, latency, connection density, service area, etc. Comprehensive sets of such requirements for different industrial scenarios are described in [26] and [41].

Decision and control over wireless networks: Problems in the inference and control over resource limited wireless networks have been studied since the 1980s and advances have been made on several fundamental questions. The authors of [37] survey the classical literature on inference and control over wireless, pointing out that these papers consider limited abstractions, relax an ideality in the original model, and provide a complete rigorous analysis. The problems arising in practice would have many aspects to consider in the same formulation: e.g., the effect of communication nonidealities on the controlled system, and also the management

[1]The acronym "PHY" refers to the technologies at the *physical layer*, i.e., the technologies used for transmitting information bits over a physical medium, such as an optical fibre or a radio frequency (RF) channel.

[2]A Basic Service Set (BSS) is an access point (AP) along with all its associated stations (STAs).

[3]Transmission Control Protocol: the end-to-end procedures in the Internet that provide a reliable transfer service over the unreliable packet transfer service provided by the Internet.

of the wireless network. They point out that it will, in general, be prohibitively expensive to match wireline quality of service over wireless networks. But in many applications, the QoS provided by wireless networks might suffice, with proper design of the wireless network controls, and of the controls that run over the wireless network. The designs will be situation dependent, and, in general, it would be interesting (though complex) to consider joint design of the controls of the network and control over the network.

A formulation of statistical decision making over a wireless network has been studied in [25], where the decision to send the command is based on the feedback of the channel condition.

The authors of [36] consider a linear time invariant system, with Gaussian plant and observation noise, and quadratic loss. The observations and the control commands can be lost in the wireless network. They show that classical separability holds only if the plant acknowledges the receipt of a control command or loss thereof. Further, the system is stabilisable only if the loss probabilities are lower than certain thresholds. [31] also consider a system similar to the one studied in [36], but they include random delays in the wireless network, both for the observations and the control commands.

The authors of [24] jointly optimize sampling, control, congestion control and scheduling policies. The paper [28] considers multiple remote estimation systems equipped with a common auxiliary channel at a lower frequency band, and provides an algorithm to decide which node should use the auxiliary channel, in order to jointly optimize estimation error and energy consumption. Age of Information (AoI) based transmission scheduling and control have been analysed in [27, 15]. Finally, the paper [3] proposes a *distributed value-of-information* metric for scheduling and control where multiple control loops share the same wireless medium.

QoS management of Wi-Fi networks: IEEE 802.11ax (High Efficiency WLAN (HEW)), introduces techniques such as Spatial Reuse [42, 39] where the aim is to dynamically manage the transmission power and the carrier sense threshold when there are overlapping BSSs. Another feature called Target Wake Time (TWT) [30] is introduced, where an AP negotiates sleep-wake schedules with an associated STA or group of STAs such that the STA or group of STAs are active only in their respective wake periods and in sleep otherwise, thus reducing contention. However, there appear to be no network-wide mechanisms to utilize either Spatial Reuse or TWT to achieve globally optimal network performance. Also, the efficient implementation of these features requires coordination across APs the network. IEEE 802.11be (Wi-Fi 7, or Extremely High Throughput (EHT)) proposes Multi-AP coordination [5] which is expected to enable these features.

5G-NR networks for factory automation: 5G-NR is designed with many new capabilities and features such as a wide range of radio bands, carrier aggregation, dynamic MAC, and sub millisecond slot scheduling, in principle capable of delivering ultra-high (aggregated) peak bit rates and ultra-low latency [32]. In the existing 5G standard, a flow-based QoS framework is utilised, incorporating a new Service Data Adaptation Protocol (SDAP) sub-layer for mapping flows with specific QoS requirements to preconfigured Data Radio Bearers (DRBs), which, in turn, by configuring the MAC scheduler to provide various QoS profiles [43]. In [23], the simulation studies show the requirement of a high density of 5G radio units (RU) to cover a factory floor to support the QoS requirement under URLLC (Ultra Reliable Low Latency). However, this dense deployment may result in significant cost inefficiencies.

Wi-Fi 5G-NR convergence: Standards bodies have defined policies and architecture to enable the interworking of 5G and Wi-Fi access networks [2]. As per the architecture proposed, the Wi-Fi network is connected to the 5G core via a gateway function called N3IWF as shown in Fig-3. It supports authentication, transportation of data and management of the 5G UEs connected through the Wi-Fi network. The N3IWF communicates with the AMF/SMF (two signalling and session management related core functions

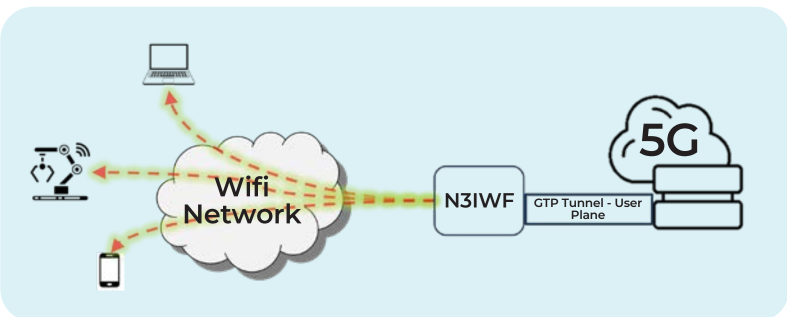


Fig-3: Wi-Fi and 5G convergence based on the N3IWF module

in 5G systems) to receive the QFI (QoS Flow Indicator) to 5QI mapping. It creates the IPSec (secure IP) tunnels based on QoS flows required and forwards the traffic into appropriate IPSec tunnel based on the QFI.

- ***Our Own Related Contributions***

Control of and inference over wireless networks: On the topic of control of a wireless network that connects sensors to a sink, in [29] we have developed a new reduced delay MAC (Medium Access Control) in which there is no centralised controller, and only a one-bit information snooping suffices to carry out the scheduling actions. In [34] we consider several sensors observing a random process that, at a random time, changes its statistics. The problem is to make an optimal Bayesian inference of the change point, trading off the probability of false alarm against the mean delay in detection. We show that the classical Shirayev algorithm needs to be modified by solving the partially observed MDP (Markov Decision Process) "from scratch," yielding a different algorithm. In [9], we continue work in change-point detection over a wireless network, except that here we consider the non-Bayesian framework. We find that the optimal decision rule needs to incorporate the random process of network losses. Further, we study the effect of service policy in the wireless queue at the sensor.

Age-of-information: We have developed [17], optimal sensor sampling and transmission scheduling algorithms to minimize age-of-information (AoI) in a single source single sink system equipped with energy harvesting capability and operating over a wireless link. This work was later extended in [21] to handle the problem of unknown wireless link characteristics and unknown energy harvesting statistics. In our subsequent works [19, 22], we had developed joint sensor scheduling and sampling algorithms for AoI minimization in a multi-source single-sink system equipped with energy harvesting sensors. Further, nonstationary energy harvesting rate and channel statistics were handled in [18], [20], where we had numerically demonstrated that the *regret* of the proposed transmission scheduling algorithm with respect to a benchmark algorithm is small.

Security of networked inference systems: We have also worked on false data injection (FDI) attacks on remote state estimation systems. Our work [8] developed secure state estimation algorithms in presence of FDI, as well as FDI detection algorithms, for a remote state estimation system comprising multiple sensors communicating with a remote state estimator. Later, our work [14] developed the quickest change detection algorithm against FDI attack in this setting. For distributed state tracking systems, our work [13] designed FDI attack in order to steer the state estimates at various sensors to a target value, under a constraint on the probability of attack detection. On the other hand, our work [6] has developed nearly quickest change detection algorithm for FDI on such distributed process tracking systems.

Centralised overlay control of a Wi-Fi network: In [38] we develop ADWISER which is a centralised overlay controller for a multi AP Wi-Fi network. ADWISER primarily provides global utility optimal TCP throughputs across a multi AP network, and can also manage the performance of downlink real-time flows, such as real-time video.

- ***ADWISER for Industrial Control Over Wi-Fi***

ADWISER is an overlay Wi-Fi controller introduced in [16], and extended in [40]. ADWISER manages the performance of downlink and uplink TCP flows, and downlink real-time video. All data packets for downlink TCP flows and ACK (acknowledgement) packets for uplink TCP flows are queued in per-station queues in the ADWISER controller. Downlink real-time flows are queued in separate per-station queues. ADWISER overlays periodic time-slices of, say, 20 ms duration, which are partitioned into a mini slice for releasing downlink real time UDP packets, and the remaining slice for uplink and downlink best-effort flows. In each best-effort subslice, ADWISER uses an online learning algorithm to determine a set of AP-STA pairs to release best-effort packets. After ADWISER releases data to the Wi-Fi network, normal CSMA/CA (Carrier Sense Multiple Access/Collision Avoidance) is used for transmitting the data between the devices.

For the support of industrial control, we have extended the above approach to enable the support of low latency uplink UDP[4] real-time flows. In doing this we have, essentially, provided the support of Time Sensitive Networking over Wi-Fi, in conjunction with fair access to bulk transfer TCP flows. We achieve this objective by adding uplink minislices to which the various uplink UDP real-time flows are mapped depending on their requirements. ADWISER

[4]User Datagram Protocol: the procedures used for transmitting data packets using the basic unreliable Internet packet transfer service

assigns industrial devices to their respective minislices and ensures that no best-effort flows or downlink real-time flows occupy these minislices. Uplink UDP devices are assigned to minislices and send their packets only during their assigned minislices. To achieve this, the uplink real-time devices must align their clocks with the ADWISER clock, so as to accurately determine the location, in time, of their assigned minislices. In our current implementation, due to the unavailability of Wi-Fi devices that support hardware level time-synchronisation, we have resorted to utilising Chrony, an evolution of the well-known NTP (Network Time Protocol), the classical system for time-synchronisation in the Internet. ADWISER assists Chrony in more accurate clock synchronisation by periodically allocating a minislice for Chrony to send its clock-synchronisation probe packets.

We have tested our approach with a combination of real-time uplink video, edge control of two-wheeled self-balancing robots, and bulk TCP transfers. The video is able to maintain its native frame rate, and the robots balance with tilt angle errors close to the values when their traffic is the only one occupying the Wi-Fi network.

Our approach of central coordination and orchestration, in conjunction with effective access to scheduling features in the access points can permit the support of critical industrial Cyber-Physical Systems over the ubiquitous and inexpensive Wi-Fi technology.

- ***Drone Based Sensing for Industrial Applications***

In certain applications, wired or wireless communication may not be available. For example, automated monitoring and occasional water sprinkling over a large agricultural field is an important application, but establishing a dedicated irrigation system and communication network only for this is usually not cost efficient. A viable alternative in this case is to use a drone that can sprinkle water and also gather the soil moisture information during its tour over the field. Another pressing application is detection of poisonous gas leakage in a large factory or mine, where manual data collection is risky, and establishing a dedicated sensor network is challenging due to cost or time constraints or due to the nature of the terrain. A mobile sensor such as one mounted on a drone would be a feasible solution for such applications. Design of such systems requires multi-pronged efforts: the algorithmic side alone poses several challenging problems on energy management, path planning, data compression and efficient sensing algorithm design.

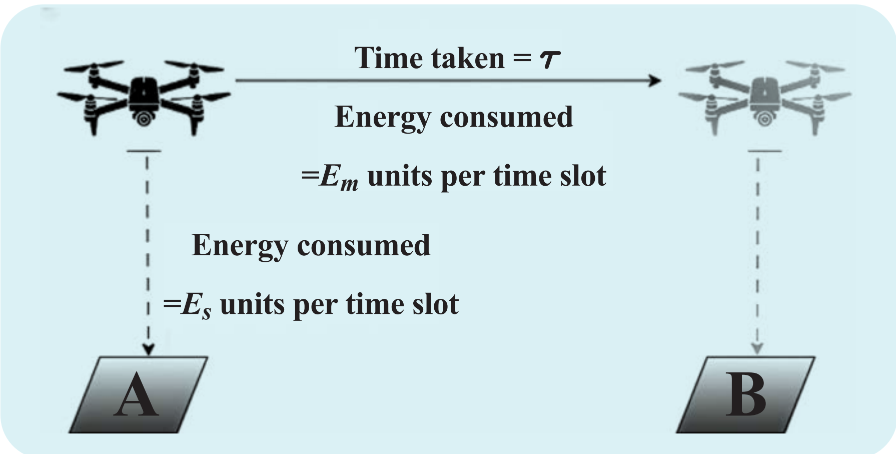


Fig-4: Quickest change detection by a sensor mounted on a drone; diagram taken from [6]

Motivated by the drone based gas leakage monitoring application, our recent work [4] addresses the problem of quickest change detection (QCD [33]) at two spatially separated locations monitored by a single drone equipped with a sensor. QCD literature deals with detecting a sudden change in the statistics in a sequential data stream, the goal typically being to minimize the *detection delay* subject to a constraint on *false alarms* wrongly triggered due to a false perception of change. In the gas leakage example, a sudden leakage would induce a change in the statistics of sensor observations. In [4], we consider an abstraction of this problem. At any of the two locations, the sensor (mounted on a drone) observes data sequentially at discrete time instants. The distribution of the observation data changes at some unknown, arbitrary time and the drone has to detect this change in the shortest possible time. Change can occur at most at one location over the entire infinite time horizon. The drone switches between these two locations in order to quickly detect the change. To this end, we propose a Location Switching and Change Detection (LS-CD) algorithm for observation-driven location switching and change detection. The primary goal is to minimize the worst-case average detection delay (WADD [33]) while meeting constraints on false alarm rate and the drone's energy consumption rate. We provide a rigorous theoretical analysis of the algorithm's performance, and derive novel upper and lower bounds to its performance metrics. Numerical simulations demonstrate the efficacy of the proposed algorithm.

- ***Detecting and Localising Drones***

While drones can effectively be used as sensors and actuators in a CPS context, there are situations in which adversarial drones need to be detected. Given the increasing use of drones, detection and localisation of drones is an important problem in many military and civil applications. While radar signal processing is a classical field, increasing applications of drones gives rise to the need for high-resolution, low power, cost-efficient radars. To this end, our recent work [35] has considered multiple-input multiple-output (MIMO) radar which offers several performance and flexibility advantages over traditional radar arrays. Specifically, we consider frequency modulated continuous wave (FMCW) radars with MIMO architecture, since it can operate at a lower peak transmit power than the traditional Pulse-Doppler radar. However, achieving high angular and Doppler resolutions necessitate a large number of antenna elements and the transmission of numerous chirps, leading to increased hardware and computational complexity. In this paper, we propose a novel compressive sensing (CS)-based multi-target localization algorithm in the range, velocity, and angular domains for MIMO-FMCW radar, where we jointly estimate target velocities and angles of arrival. To this end, we present a signal model for sparse-random and uniform linear arrays. For range estimation, we propose two different techniques, each with distinct advantages, while two-dimensional compressive sensing is used for joint velocity-angle estimation. We establish theoretical performance guarantees for the proposed algorithm. Our numerical experiments demonstrate that our methods achieve similar detection performance and higher resolution compared to conventional DFT and MUSIC with fewer transmitted chirps and antenna elements. In other words, our proposed signal processing algorithm improves radar sensing performance while reducing the hardware complexity, power consumption and computational complexity over conventional MIMO-FMCW radars.

However, it has to be noted that the work in [35] assumes point targets. In practice, radar signals scattered from drones have one additional feature that is highly useful, namely, the micro-Doppler signature [11]. Analysis of Doppler shift in the received signal reveals useful information about the velocity of the target; a translational motion with constant velocity of a point target will cause a single Doppler frequency tone in the received signal. However, a drone has an extended body. Most importantly, the distances of the propeller blades from the radar vary with time due to the blade rotation. This yields a Doppler spectrum at the receiver, which contains additional Doppler frequencies apart from that generated due to a purely translational motion. We are currently working on developing algorithms for micro-Doppler processing in MIMO-FMCW radars.

While the focus of our work has been on developing practical algorithms on radar signal processing for drone detection, theoretical development of such algorithms poses very interesting and challenging variants of classical frequency estimation problems [12], which may be of independent interest to the broader research community.

Conclusion

In this brief article we have surveyed the state of research in the important area of industrial Cyber-Physical Systems over wireless networks. At the present time most industrial process control happens over wireline networks, such as the Industrial Ethernet. Emerging applications such as the control of mobile robots and material handling vehicles, indoor and outdoor drones of a variety of sizes, and the support of surveillance cameras will require the availability of wireless networks that can provide the range of quality of service and system capacity that these applications, at scale, will require. The engineering of Cyber-Physical Systems over wireless networks, and the development and management of wireless networks that can support such applicatuons can be expected to be a challenging, emerging opportunity.

References

1. Bosch mobility: History of innovations. https://www.bosch-mobility.com/en/company/milestones/.
2. 3GPP. 5G; Access to the 3GPP 5G Core Network (5GCN) via non-3GPP access networks. Technical Specification (TS) 25.502, 3rd Generation Partnership Project (3GPP), 06 2018. Version 18.5.0.

3. Precious Ugo Abara and Sandra Hirche. Distributed value of information in feedback control over multi-hop networks. *arXiv preprint arXiv:2107.07822,* 2021.

4. Saqib Abbas, Anurag Kumar, and Arpan Chattopadhyay. Quickest change detection for UAV-based sensing. *arXiv preprint arXiv:2504.07493,* 2025.

5. Woojin Ahn. Novel Multi-AP Coordinated Transmission Scheme for 7th Generation WLAN 802.11be. *Entropy,* 22(12), 2020.

6. Saqib Abbas Baba and Arpan Chattopadhyay. Quickest detection of false data injection attack in distributed process tracking. *arXiv preprint arXiv:2402.09743,* 2024.

7. Radhakisan Baheti and Helen Gill. Cyber-physical systems. In T. Samad and A.M. Annaswamy (eds.), editors, *The Impact of Control Technology.* IEEE Control Systems Society, 2011.

8. Arpan Chattopadhyay and Urbashi Mitra. Security against false data-injection attack in cyber-physical systems. *IEEE Transactions on Control of Network Systems,* 7(2):1015– 1027, 2019.

9. Krishna Chaythanya, Arpan Chattopadhyay, Anurag Kumar, and Rajesh Sundaresan. Quickest change point detection with measurements over a lossy link. In *Proc. IEEE Conference on Decision and Control,* 2023.

10. Kwang-Cheng Chen, Shih-Chun Lin, Jen-Hao Hsiao, Chun-Hung Liu, Andreas F. Molisch, and Gerhard P. Fettweis. Wireless networked multi-robot systems in smart factories. *Proceedings of the IEEE,* 109(4):468–494, 2021.

11. Victor C Chen, Fayin Li, S-S Ho, and Harry Wechsler. Micro-Doppler effect in radar: phenomenon, model, and simulation study. *IEEE Transactions on Aerospace and electronic systems,* 42(1):2–21, 2006.

12. Yuejie Chi and Yuxin Chen. Compressive two-dimensional harmonic retrieval via atomic norm minimization. *IEEE Transactions on Signal Processing,* 63(4):1030–1042, 2014.

13. Moulik Choraria, Arpan Chattopadhyay, Urbashi Mitra, and Erik G Stro¨m. Design of false data injection attack on distributed process estimation. *IEEE Transactions on Information Forensics and Security,* 17:670–683, 2022

14. Akanshu Gupta, Abhinava Sikdar, and Arpan Chattopadhyay. Quickest detection of false data injection attack in remote state estimation. In *2021 IEEE International Symposium on Information Theory (ISIT),* pages 3068–3073. IEEE, 2021.

15. Jannik Hahn and Olaf Stursberg. Uncertain AoI in stochastic optimal control of networked and constrained lti systems. *arXiv preprint arXiv:2104.12435,* 2021.

16. Malati Hegde, S. V. R. Anand, Anurag Kumar, and Joy Kuri. WLAN manager (WM): a device for performance management of a WLAN. *International Journal of Network Management,* 17:155–170, 2007.

17. Akanksha Jaiswal and Arpan Chattopadhyay. Minimization of age-of-information in remote sensing with energy harvesting. In *2021 IEEE International Symposium on Information Theory (ISIT),* pages 3249–3254. IEEE, 2021.

18. Akanksha Jaiswal and Arpan Chattopadhyay. Age-of-information minimization for energy harvesting sensor in non-stationary environment. In *2023 21st International Symposium on Modeling and Optimization in Mobile, Ad Hoc, and Wireless Networks (WiOpt),* pages 1–8. IEEE, 2023.

19. Akanksha Jaiswal and Arpan Chattopadhyay. Age-of-information minimization for IoT systems with multiple energy harvesting sources. In *2024 IEEE Globecom Workshops (GC Wkshps),* pages 1–6. IEEE, 2024.

20. Akanksha Jaiswal and Arpan Chattopadhyay. Age-of-information minimization under energy harvesting and non-stationary environment. *arXiv preprint arXiv:2504.04916,* 2025.

21. Akanksha Jaiswal, Arpan Chattopadhyay, and Amokh Varma. Age-of-information minimization via opportunistic sampling by an energy harvesting source. *IEEE Transactions on Cognitive Communications and Networking,* 10(6):2296–2310, 2024.

22. Akanksha Jaiswal and Arpan Chattopadhyay. Whittle's index-based age-of- information minimization in multi-energy harvesting source networks. *arXiv preprint arXiv:2408.02570*, 2024.

23. Mostafa Khoshnevisan, Vinay Joseph, Piyush Gupta, Farhad Meshkati, Rajat Prakash, and Peerapol Tinnakornsrisuphap. 5G industrial networks with CoMP for URLLC and time sensitive network architecture. *IEEE Journal on Selected Areas in Communications,* 37(4):947–959, 2019.

24. Markus Klu¨gel, Mohammadhossein Mamduhi, Onur Ayan, Mikhail Vilgelm, Karl H Johansson, Sandra Hirche, and Wolfgang Kellerer. Joint cross-layer optimization in real- time networked control systems. *IEEE Transactions on Control of Network Systems,* 7(4):1903–1915, 2020.

25. Markus Klu¨gel, Mohammad H. Mamduhi, Onur Ayan, Mikhail Vilgelm, Karl H. Johansson, Sandra Hirche, and Wolfgang Kellerer. Joint cross-layer optimization in real-time networked control systems, 2019.

26. Andrew Kusiak. Smart manufacturing. *International Journal of Production Research,* 56(1-2):508–517, 2018.

27. Polina Kutsevol, Onur Ayan, and Wolfgang Kellerer. Control-aware scheduling over multi-hop networks. *Journal of Communications and Networks,* 25(5):688–698, 2023.

28. Zitian Li, Lixin Yang, Yijin Jia, Zenghong Huang, Weijun Lv, and Yong Xu. Optimal scheduling for remote estimation with an auxiliary transmission scheme. In *IEEE Conference on Decision and Control (CDC).* IEEE, 2023.

29. Avinash Mohan, Arpan Chattopadhyay, Shivam V. Vatsa, and Anurag Kumar. A low-delay mac for iot applications: Decentralized optimal scheduling of queues without explicit state information sharing. *IEEE Transactions of Control of Network Systems,* to appear.

30. Maddalena Nurchis and Boris Bellalta. Target Wake Time: Scheduled Access in IEEE 802.11ax WLANs. *IEEE Wirel. Commun.*, 26(2):142–150, 2019.

31. Marijan Palmisano, Martin Steinberger, and Martin Horn. Optimal finite-horizon control for networked control systems in the presence of random delays and packet losses. *IEEE Control Systems Letters,* 5(1):271–276, 2021.

32. Stefan Parkvall, Erik Dahlman, Anders Furuskar, and Mattias Frenne. NR: the new 5G radio access

technology. *IEEE Communications Standards Magazine,* 1(4):24–30, 2017.

33. H Vincent Poor and Olympia Hadjiliadis. Quickest detection. *Cambridge*, UK, 2009.

34. K. Premkumar, V. K. Prasanthi, and Anurag Kumar. Delay optimal event detection on ad hoc wireless sensor networks. *ACM Transactions on Sensor Networks,* March 2012.

35. Chandrashekhar Rai, Himali Singh, and Arpan Chattopadhyay. Multi-target range, doppler and angle estimation in MIMO-FMCW radar with limited measurements. *accepted in IEEE Transactions on Signal Processing, https: // ieeexplore. ieee. org/ stamp/ stamp. jsp? tp= &arnumber= 11163723* , 2025.

36. Luca Schenato, Bruno Sinopoli, Massimo Franceschetti, Kameshwar Poolla, and S. Shankar Sastry. Foundations of control and estimation over lossy networks. *Proceedings of the IEEE,* 95(1):163–187, 2007.

37. Lucas Scheuvens, Meryem Simsek, Andr´e Noll-Barreto, Norman Franchi, and Gerhard P. Fettweis. Framework for adaptive controller design over wireless delay-prone communication channels. *IEEE Access,* 7:49726–49737, 2019.

38. Vishal Sevani, Purushothaman Saravanan, S. V. R. Anand, Joy Kuri, and Anurag Kumar. Time-slicing high throughput Wi-Fi networks using centralized queueing and scheduling. WiNTECH, page 53–60, 2022.

39. Zhao Shen, Bo Li, Mao Yang, Zhongjiang Yan, Xiaobo Li, and Yi Jin. Research and Performance Evaluation of Spatial Reuse Technology for Next Generation WLAN. In Jiann-Liang Chen, Ai-Chun Pang, Der-Jiunn Deng, and Chun-Cheng Lin, editors, *Wireless Internet,* pages 41–51, Cham, 2019. Springer International Publishing.

40. Shivam V. Vatsa, G. P. Anusha, Vishal Sevani, Purushothaman Saravanan, Rahul Nair, Rishabh Roy, S. V. R. Anand, Joy Kuri, and Anurag Kumar. Optimum MultiAP coordination in Wi-Fi with overlay time-sliced scheduling. *IEEE/ACM Transactions on Networking.* DOI:https://doi.org/10.1109/TON.2025.3613824.

41. Jiafu Wan, Baotong Chen, Muhammad Imran, Fei Tao, Di Li, Chengliang Liu, and Shafiq Ahmad. Toward dynamic resources management for IoT-based manufacturing. *IEEE Communications Magazine,* 56(2):52–59, 2018.

42. Francesc Wilhelmi, Sergio Barrachina Mun˜oz, Cristina Cano, Ioannis Selinis, and Boris Bellalta. Spatial reuse in IEEE 802.11ax WLANs. *Computer Communications,* 170, March 2019.

43. Zhi-Li Zhang, Udhaya Kumar Dayalan, Eman Ramadan, and Timothy J. Salo. Towards a software-defined, fine-grained qos framework for 5G and beyond networks. In *Proceedings of the ACM SIGCOMM 2021 Workshop on Network-Application Integration,* NAI'21, page 7–13, New York, NY, USA, 2021. Association for Computing Machinery.

Memberships of INAE
Connecting Academia, Industry & Engineering Professionals

The Indian National Academy of Engineering (INAE), a premier Academy, dedicated to the advancement of engineering and technology in India, offers three primary categories of membership—Institutional Membership, Corporate Membership, and Individual Membership. These membership types are designed to bring together academia, industry, and the professional engineering community, encouraging collaboration, innovation, and thought leadership in engineering-related fields. To have a wider reach and participation of engineering community, these new streams of membership of INAE have been instituted recently.

Institutional Membership:

Institutional Membership of INAE is offered to academic and research institutions, including universities, colleges, engineering institutes and R&D organizations that are actively engaged in scientific and technological pursuits. This membership category is aimed at strengthening linkages between INAE and institutions that contribute significantly to engineering education, research, and innovation. Institutional Members benefit from opportunities to participate in national conferences, symposia, and technical events organized by INAE. They also receive access to a wide range of INAE publications, policy papers, and technical reports, and gain opportunities to collaborate on engineering initiatives and national missions. This membership serves as a platform for institutions to contribute to shaping the national engineering agenda and to engage with a larger network of experts and decision-makers.

Click/Scan for more details

Corporate Membership:

Corporate Membership of INAE is intended for companies and industrial organizations engaged in engineering, manufacturing, infrastructure, technology development, or consultancy. Corporate Members benefit from a close association with INAE Fellows, policymakers and academic institutions on issues of engineering interest. They gain access to workshops, panel discussions, and policy dialogues where critical issues at the intersection of technology, industry, and national development are addressed. This membership will also enable companies to nominate outstanding engineers for recognition by INAE and provide them a platform to contribute to national-level discussions on industry-relevant challenges. Moreover, Corporate Members can actively participate in fostering industry-academia collaboration, contributing to curriculum development, mentorship, and joint R&D initiatives.

Click/Scan for more details

Individual Membership:

Though the Fellowship of INAE is the gold standard of recognition for notable engineers, who are elected by a rigorous three-tier process by expert committees of the Fellowship, however, in order to encourage a wider reach and participation of engineering community, Individual Membership has been recently introduced at INAE. The Individual Membership is accorded to professionals working in engineering and technology in industry, R&D or academic institutions, engineering services, entrepreneurship firms and government/private agencies by a selection process. All Individual Members benefit from recognition by the Academy and provides a platform for networking opportunities. A special program 'Technology Conclave' has been curated for the Members of INAE. Members are also invited for the INAE's flagship events held every year.

INAE currently offers Senior and Associate Memberships, to engage engineers at different stages of their careers. Senior Membership is awarded to experienced professionals with significant experience in engineering community. Associate Membership is aimed at promising mid-career engineers with opportunities for participation in INAE activities. Together, these categories support a structured growth pathway within India's engineering ecosystem.

Click/Scan for more details

INAE's membership structure is designed to build a vibrant, interconnected community of institutions, companies, and individuals who are committed to advancing engineering and technology for national development. Through its diverse membership base, INAE fosters interdisciplinary collaboration, provides a platform for dialogue on critical technological issues and promotes excellence in engineering practice and education across India and beyond.

A significant new initiative launched by INAE is the quarterly e-Magazine TechFrontier, conceived to showcase emerging trends, impactful research, and technological innovations in engineering and technology. The magazine was successfully launched on April 20, 2025, during the INAE Foundation Day.

This digital publication is envisioned as a platform to highlight cutting-edge advancements from India and across the globe. Its objective is to create awareness about engineering and technology by publishing articles on futuristic, emerging, and high-impact technologies that appeal not only to the engineering community but also to readers outside the field who have an interest in science and technology.

Volume I, Issue I of INAE TechFrontier, centred on the theme "Quantum Technology: India-centric Policy Perspectives", was successfully launched on April 20, 2025, during the INAE Foundation Day function held at IIT Delhi. The inaugural issue received an encouraging response and set a strong precedent for future editions. The issue features invited articles highlighting indigenous products, technological breakthroughs, and conceptual or review contributions that collectively reflect the cutting-edge advancements taking place in the country in the field of quantum technology.

Click/Scan for TechFrontier Volume I, Issue I

Volume I, Issue II of INAE TechFrontier focuses on the theme "Manufacturing", a sector that forms the backbone of India's aspirations for technological self-reliance, global competitiveness, and sustained economic growth. As the nation advances toward becoming a major innovation-driven economy, the manufacturing ecosystem encompassing advanced materials, automation, digitalisation, and sustainable production continue to evolve rapidly.

This edition features a thoughtfully curated collection of insightful articles that showcase the diversity, depth, and transformative potential of manufacturing-related research and development underway across the country.

Click/Scan for TechFrontier Volume I, Issue II

About INAE:

The Indian National Academy of Engineering (INAE), founded on April 20, 1987 as a Society under the Societies Registration Act, is an autonomous professional body located at Technology Bhawan, New Delhi. It comprises India's most distinguished engineers, engineer-scientists and technologists covering the entire spectrum of engineering disciplines. INAE functions as an apex body and promotes the practice of engineering & technology and the related sciences for their application to solving problems of national importance. The Academy also provides a forum for futuristic planning for country's development requiring engineering and technological inputs and brings together specialists from such fields as may be necessary for comprehensive solutions to the needs of the country. The actionable recommendations emanating from the deliberations of technical events and programs are submitted to the concerned government Departments/Agencies for consideration as inputs for framing of national policies. As the only engineering Academy of the country, INAE represents India at the International Council of Academies of Engineering and Technological Sciences (CAETS); a premier non-governmental international organization comprising of Member Academies from 33 countries across the world, with the objective of contributing to the advancement of engineering and technological sciences to promote sustainable economic growth.

Indian National Academy of Engineering

Ground Floor, Block-II, Technology Bhawan, New Mehrauli Road, New Delhi-110016 (India)

Ph. +91 11 26582475 email: inaehq@inae.in