

# Digital Twin

Optimizing KPIs in Discrete Manufacturing with Advanced Engineering Analytics and Cyber-Physical Systems

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CONSULTANCY  
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## IN BRIEF

In discrete manufacturing, optimizing KPIs is a challenge as there are conflicting goals and constraints at each plant and site level. Process automation systems, from the traditional product quality control, are reactive in nature. Now, there is an opportunity to move toward proactive methods. Multiple systems collect data, and many global organizations have started leveraging cloud and IoT to gather and collate that data. An autonomous cyber-physical system that can work in tandem with a physical entity taking real-time data and providing real-time decisions can optimize KPIs.

Development of this system, the digital twin, requires various data mining and analytics activities in addition to modeling, optimization, and control. Toward this end, we have developed a framework for engineering analytics that performs end-to-end analysis and provides recommendations to help improve operations. Apart from building digital twins of various plants, we hope to extend this platform to design new materials and for predictive maintenance of equipment.

The performance of continuous or discrete manufacturing or process industries is commonly evaluated in terms of key performance indicators (KPIs) related to production operations, asset or equipment health and reliability, climate change regulations, and safety of the personnel. The typically measured KPIs include productivity, throughput, product quality, specific energy consumption (fuel and/or electricity), cost of production, specific waste (solid/liquid) generation, plant or equipment availability, specific

consumption of raw materials and utilities (water, steam, etc.), equipment maintenance cost, number of accidents or incidents, specific emission of pollutants such as carbon monoxide/dioxide, NOx, SOx, etc. These KPIs depend on the availability and quality of raw materials, condition or health of the equipment and instruments used in the production operations, actual operating conditions, and environmental conditions. Process automation and control systems also play a crucial role in this regard.

## Fact File

**TCS Research:** Research & Innovation for Manufacturing & Engineering

**Outcomes:** Development and deployment of advanced modeling and analytics solutions and digital twins in diverse industries

**Principal Investigator:** Venkataramana Runkana

**Academic Partners:** Columbia University in the City of New York, IIT Kanpur, IIT Bombay and IIT Delhi

**Techniques Used:** Physics-based Modeling; Machine Learning; Multi-objective Optimization; Advanced Process Control

**Industries Benefited:** Power Plants, Minerals and Metals; Chemicals; Automotive; Pharmaceuticals; Medical Devices; Oil & Gas; CPG

**Patents:** 25 filed, 7 granted

**Chapters in Books:** 6

**Journal Papers:** 24

**Conference Presentations:** 60

### Toward quality first

Achieving optimum values of the KPIs is an exercise in multiobjective optimization with conflicting goals and constraints at the plant/site level. This is a challenging and complex task because of the inherently dynamic nature of industrial scale operations, large number of process variables involved and their inter-relationships. Moreover, one has to deal with raw materials from multiple sources with widely varying characteristics. Further, there is also a need to manufacture products with different quality specifications using the same or similar set of equipment.

While process automation systems such as DCS (Distributed Control System), SCADA (Supervisory Control and Data Acquisition), and MES (Manufacturing Execution System) currently take care of real-time control of individual units/

subsections in a plant, there is a conscious move toward plant-wide optimization and control of KPIs globally. Similarly, industries are making an effort to move from the traditional product quality control that is reactive in nature to product quality assurance that is inherently proactive.

### Sensing equipment health

The condition of the equipment keeps deteriorating with time (e.g., wearing of mechanical components in pumps and compressors, fouling of heat exchangers, accretion in cement and sponge iron rotary kilns, ash deposition on boiler tubes). While condition-based monitoring (CBM) and reliability centric maintenance are being practiced now, efforts are being made to build predictive models for equipment health and performance so as to put predictive maintenance into practice.

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Real-time process and equipment health monitoring is done through thousands of sensors placed at locations across the whole plant whereas raw material or product quality is evaluated through inline or offline sampling and analyses in the laboratory. However, not completely new, soft-sensors are gaining acceptance in industrial practice. Development of high-fidelity soft-sensors centred on physics-based models is one of the major challenges. Similarly, wireless and noninvasive sensors are also being used, especially for equipment health monitoring.

**Global operations reach for cloud**

Many industrial organizations have their operations spread globally across different geographies.

Running the enterprises profitably may require sourcing of raw materials from one or more geographies, manufacturing of products in a different geography, and selling the products in a completely different geography (not necessarily where they are produced). Supply chain optimization and control plays a major role in this, in addition to operating the manufacturing units efficiently. Since the enterprise operations are spread globally, accessing, collecting, and integrating data from multiple plants/sites using cloud and IoT (Internet of Things) platforms is gaining importance and is already being practiced by digitally progressive organizations.

While there is a move toward the development of digital threads for

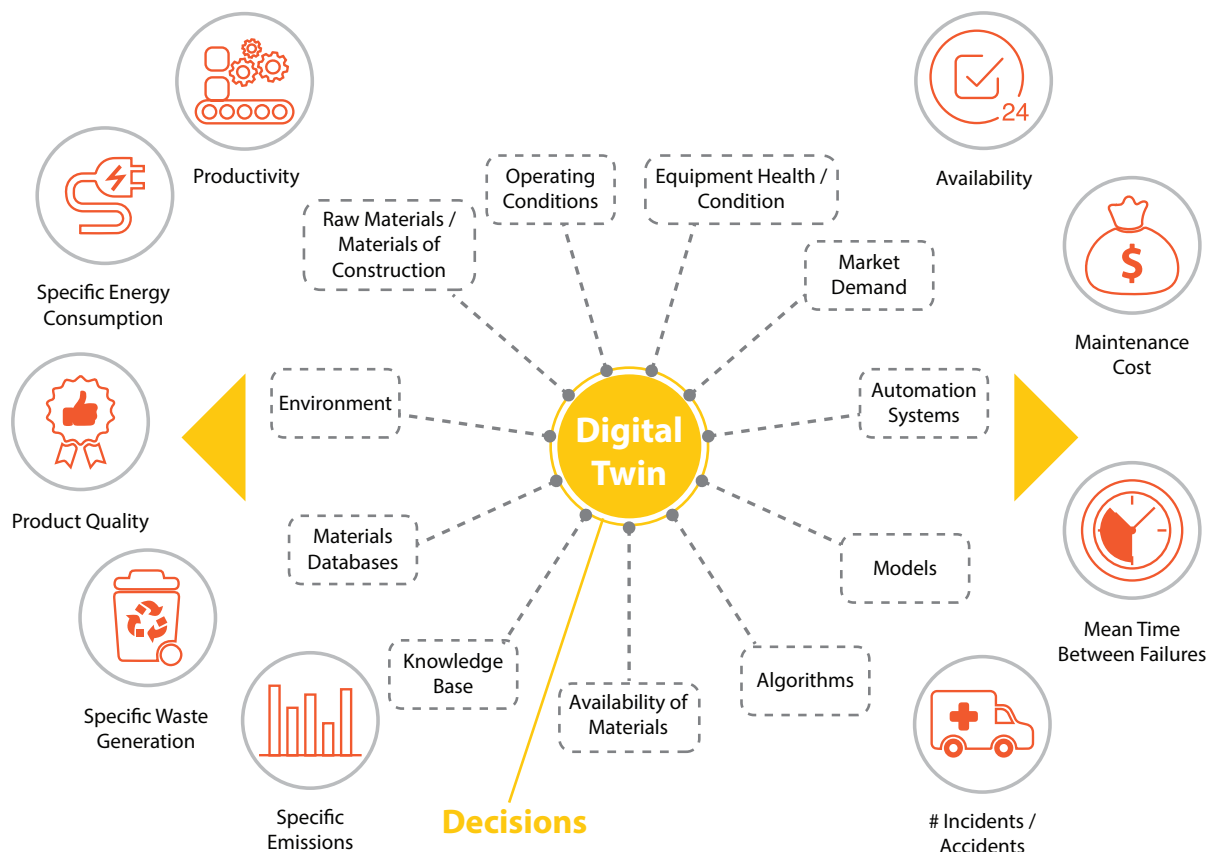


Figure 1: Schematic of a digital twin for manufacturing processes and equipment

product life cycle management, from design and manufacturing to end use, development and deployment of digital twins for manufacturing equipment and processes is heralding a completely new paradigm in the process and manufacturing industries.

### An autonomous cyber-physical system

A digital twin is an autonomous cyber-physical system working in tandem with a physical entity taking real-time data and providing real-time decisions for optimization of KPIs. It is expected to have

real-time visibility into operations and condition of equipment; information and knowledge about materials being used for processing and their properties, environmental conditions, and market demand among others. That would help provide appropriate recommendations for optimizing KPIs and for keeping the controlled variables at their optimum values.

### Current research at TCS

We have been involved in the application of predictive analytics for industrial operations in diverse industries such as

## Process and Equipment Analytics for Optimization and C(K)ontrol

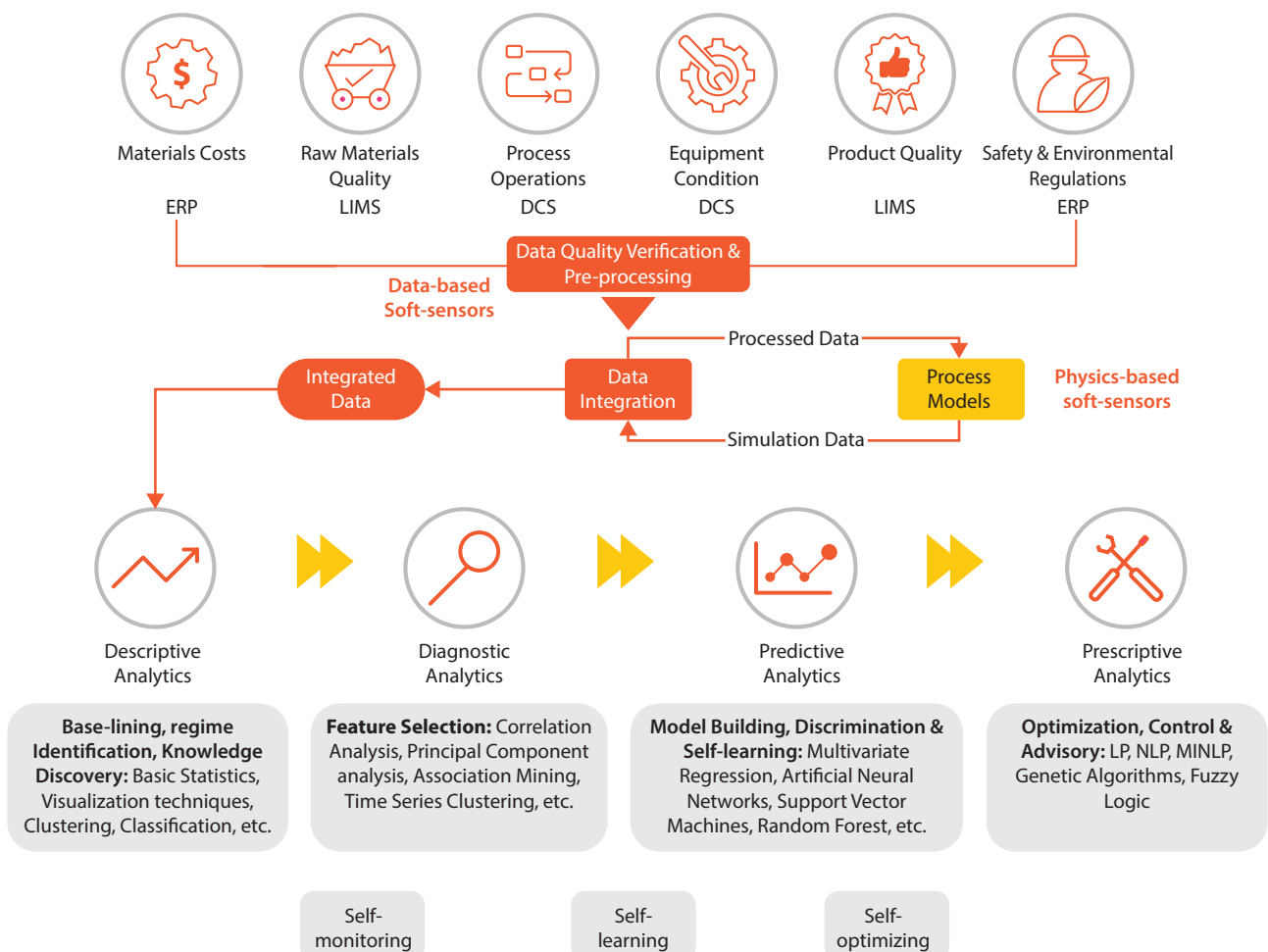


Figure 2: TCS PEACOCK Framework

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chemicals, minerals and metals, power, oil and gas, utilities, pharmaceuticals, medical devices. Some of the models we employ include physics-based, data-based, qualitative and heuristics, hybrid phenomenological and statistical models. These models are then incorporated as intrinsic components of digital twins for different processes or equipment.

Process and manufacturing industries are well instrumented and huge amounts of data are collected through various sensors in the plant and through laboratory analyses of samples. Industries use software systems such as LIMS (Laboratory Information and Management Systems), SCADA, DCS, MES, MOM (Manufacturing Operations Management), and ERP (Enterprise Resource Planning) for this purpose.

### TCS PEACOCK

Development of a digital twin requires various data mining and analytics activities in addition to modeling, optimization, and control. Toward this end, we have developed TCS PEACOCK (Process and Equipment Analytics for Optimization and Control, see Figure 2)—a framework for engineering analytics. TCS PEACOCK can carry out data mining and analytics offline and create digital twins of various processes and equipment. The important components of this framework are the Data Quality Verification System (DQVS), Data Pre-processing System (DPPS), Data Fusion/Integration, Descriptive Analytics, Diagnostic Analytics, Predictive Analytics, and Prescriptive Analytics. The framework is useful for carrying out end-to-end analytics, starting with raw data from sensors in a manufacturing or process plant to prescriptive analytics for coming up with recommendations for improving operations in terms of the

KPIs (either for a process or for an equipment).

The TCS PEACOCK framework has been successfully applied for pelletization and sintering of iron ores, prediction of silicon content in hot metal from blast furnaces, production of sponge iron in a rotary kiln, optimization of commissioning of industrial boilers, anomaly detection in the operation of gas turbines, failure detection of progressive cavity pumps, and global optimization of a mineral processing plant.

### Future research directions

We are currently developing a generic software platform based on the PEACOCK framework. The platform has been designed for off-line data mining and analytics activities using historical data, and creating and deploying digital twins that can be configured and customized easily for different industrial applications.

Based on our knowledge and experience of developing solutions for different industries, the generic PEACOCK platform is being configured and customized concurrently for different industrial sectors. The aim is to create industry-specific solutions with provisions for incorporating the appropriate domain knowledge from respective industries such as iron and steel, mining and mineral processing, petroleum refineries, power plants, and pharmaceutical manufacturing.

Development of new materials is an expensive and a relatively long-term activity. We are now planning on employing the PEACOCK platform to design new alloys or materials using machine learning and deep learning techniques. The data generated from laboratory scale

## Digital twin for a coal-fired boiler

Boilers play a critical role in thermal power plants. The three main goals for a boiler engineer are operating the boiler at its maximum efficiency, ensuring safe operation of the boiler, and keeping the emissions within the regulatory limits. One of the major challenges is the availability of good quality coal. The plant engineers are tasked with blending coals from different sources appropriately so as to achieve these primary goals. In collaboration with a technology provider, TCS

has developed a digital twin for a coal-fired boiler (see Figure 3) that combines artificial intelligence, physics of the phenomena involved and domain knowledge of operating the boilers. This system was deployed at multiple power plants in Taiwan and Japan, and has helped reduce both emissions and the cost of power production.

experiments and industrial scale operations can be leveraged to reduce effort from human experts.

Predictive maintenance of equipment is another field which could benefit from combining deep learning, machine learning, physics-based models, and domain knowledge for undertaking structured as well as unstructured (text, images and video) data analytics.

One of the focus areas of our research will be on incorporating intelligence and automation, combining with domain knowledge, in all data science activities. This is likely to help not only in reducing the time and effort for carrying out analytics, but also in building representative predictive models accurately for real-life industrial data.

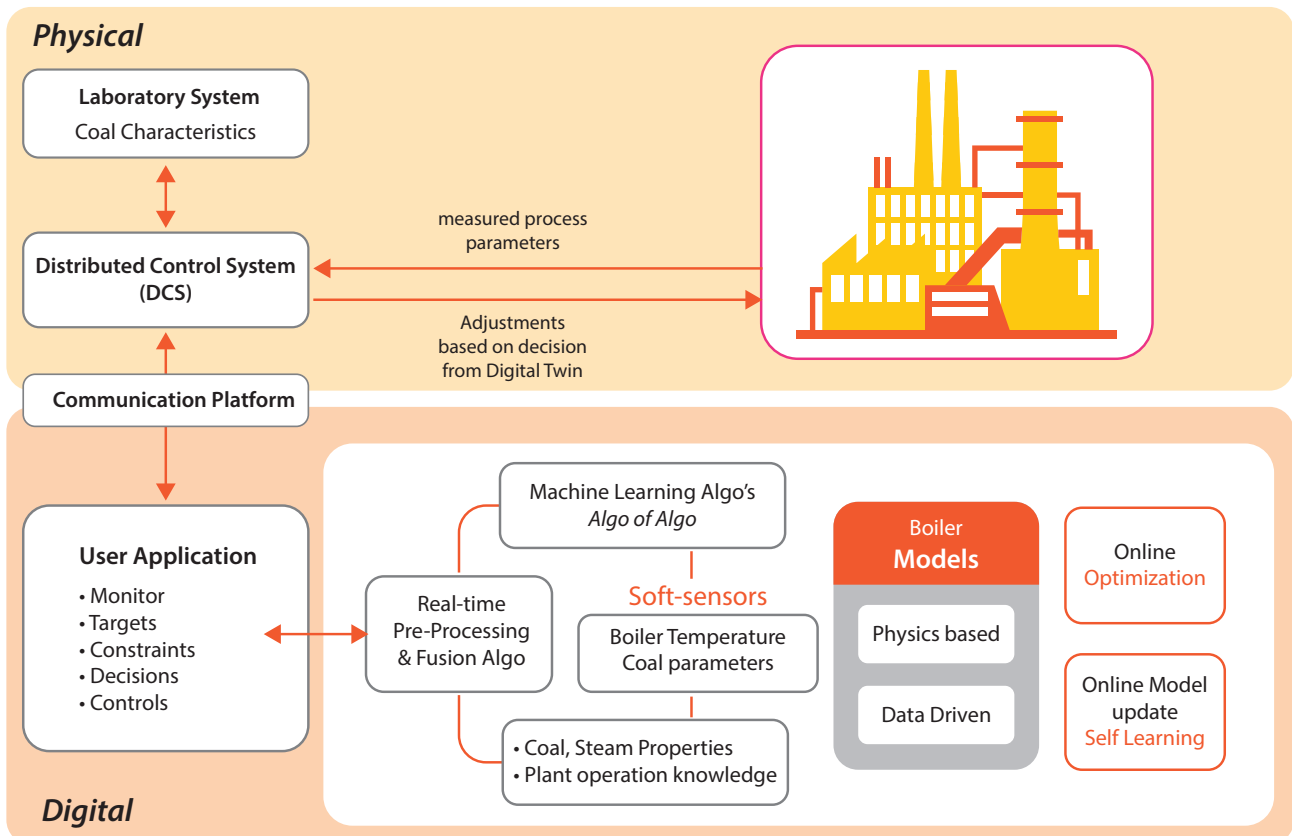


Figure 3: Digital twin for boiler



## Venkataramana Runkana

Venkataramana Runkana is a Chief Scientist at TCS Research and Innovation and heads the Research Programme for Manufacturing & Engineering and Industrial Services Business Units in TCS. Venkat has more than 27 years of experience in process modeling, simulation and optimization, advanced data analytics and digital twins, process development, scale-up and design, nanomaterials and drug delivery systems. Venkat received the TCS Distinguished Scientist Award in 2014 and was an AICTE-INAE Distinguished Visiting Professor at IIT Kanpur during 2013-2018. Venkat and his team received the Tata Group level innovation award, Tata Innovista for Implemented Innovations, and the IT Innovation Award from Express IT Awards in 2018 for their work on digital twin technology. Venkat's team has also won the Prognostics and Health Management (PHM) Society Data Challenge Competition in 2018. Venkat is a chemical engineer and holds a Ph.D. from Columbia University, New York.

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